Examination of vulnerable road users conflict severity in shared space using a mixed logit model with heterogeneity

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Abstract

Walking, cycling and riding electric bicycles (e-bikes) are popular these years, especially the e-bikes. Shared space was proposed for vulnerable road users (VRUs). Shared spaces might provide a less stressful experience for users, but frequent interactions among users present safety issues. How to define the severity of the conflict and what are the influencing factors of the conflict severity are urgently needed to know. A total of 4426 road users were observed, and 335 conflicts were recorded by Dutch Objective Conflict Technique for Operation and Research (DOCTOR) method. 23 crash points involving e-bikes that occurred in shared space during April 2013 to September 2019 were screened out, as supplementary evidence for this study. A mix logit model was established, and significant influencing factors were identified, such as female, age, traffic volume of pedestrians, and traffic volume of e-bikes. Further discussion about e-bikes show that e-bikes are more likely to get involved in conflicts than conventional bicycles. Meantime, pedestrians are mainly affected in e-bike conflicts. The crashed data proved that the e-bikes take more responsibility in shared space crashes. These findings all shows the risky of e-bikes at shared space. Speed limit and regulating the behavior of e-bikes may be effective measures to solve this problem.

Keywords: Vulnerable road users; Shared space; Traffic conflict severity; Influence factor; Mix logit model.

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1. Introduction

Walking, cycling and riding electric bicycles (e-bikes) are used by more and more people as green and environmentally friendly ways of travel [1]. In particular, e-bikes is widely used in China, Europe, Japan and the US, as a new environmental and efficient transportation mode. However, the conflict and safety of vulnerable road users (VURs) has not been paid enough attention. The urban traffic planning has been plan from the perspective of motorized traffic in recent decades, largely ignoring the VURs. Recently, a concept named shared space is proposed to improve the safety of VRUs. A shared space is defined as "a street or place designed to improve pedestrian movement and comfort reducing the dominance of motor vehicles and enabling all users to share the space rather than follow the clearly defined rules implied by more conventional designs [2].

Shared spaces are regions where there is no clear separation between road users, and all road users share the right of way. The concept of boundary is blurred in the shared space, so all kinds of road users devote more energy to ensure safety [3]. At the same time, VRUs are given more freedom, which makes them travel more comfortablely. In counterpoint to these advantages, more conflicts may be caused, which will bring security risks to vulnerable groups. Pedestrians may be exposed to more risks [4-7]. Therefore, it is necessary to analyze the conflict characteristics and conflict severity influencing factors of VRUs in shared space.

In terms of methodology, the multinomial logit (MNL) model is the most common method for injury severity analysis [7-9]. The multinomial logit model assumes that the influence of each variable is always fixed in all conflicts [10, 11]. This hypothesis is not always correct due to the unobserved heterogeneity. A mixed logit model is proposed to solve this problem [12]. Each parameter in a mixed logit model is permitted to fluctuate between observations while adhering to a prescribed distribution form. Many studies have also proved that the mixed logit model fits better and more effective than the traditional multinomial logit model [13-15].

Most of the existing studies focus on motor vehicle safety or the conflict between nonmotor vehicles and motor vehicles. The research on the conflict and safety between VRUs is very scarce. E-bikes have been widely used in recent years, but little is known about the risk of e-bikes. To fill this gap, this study investigated the VRUs conflict severity and its' influence factor in shared space using a mixed logit model with heterogeneity. The objectives are: (1) to establish a mixed logit model of conflict severity and determine its significant influencing factors; (2) to analyze the conflict characteristics of e-bikes in detail; (3) to analyze the risk characteristics of e-bikes by combining conflict data and accident data.

The rest of the study is organized as follows. Section 2 shows the DOCTOR method and mix logit model. Section 3 presents the result of the mix logit model and the significant influencing factors. The conflict characteristics and risk characteristics were discussed in Section 4. Finally, the conclusion and provides recommendations for future research were presented in Section 5.

2. Methodology

2.1. Traffic conflict identification and event coding

The Dutch Objective Conflict Technique for Operation and Research (DOCTOR) method was improved according to characteristic of VRUs conflict and used in this study. The high likelihood of a collision if the direction or speed of user does not change is the key prerequisite for identifying a conflict when using DOCTOR method. Evasive action, available space, time-to-collision (TTC), and post-encroachment time (PET) are also recorded as the supplementary prerequisite. The likelihood of a collision and the severity consequences of a potential collision are used to assess the severity of a conflict. The scoring details of conflict severity are different from the DOCTOR method because of the discrepancies between VRUs and motor vehicles. The conflict severity was then scored on a scale of 1–5. The specific scoring criteria are shown in Table 1 [16].

Table 1: Classification of conflicts by severity

Conflict severity class	Definition
1	Precautionary evasive action with a low collision probability
2	Controlled evasive action to avoid a collision with ample maneuvering time and space
3	Strong evasive action to basically avoid a collision with relatively ample maneuvering time and space

4	Emergency evasive action or uncontrolled evasive action just to avoid collision with little maneuvering time and space
5	Emergency evasive action resulting in a near-crash or slight collision

In addition, the road user type, estimated speed, type of evasive action, whether an evasive action was controlled, etc. are also recorded. All these various variables are recorded by two observers through watching the video recordings repeatedly. The coding rules for variables are shown in Table 2. Non-controversial conflicts are coded, whereas doubtful conflicts are coded following debate by the two analysts. Methods utilised to validate the consistency and reliability of traffic conflict coding refer to Huertas-Leyva et al. (2018). Events from certain random conflicts are coded twice, in two 10-day sessions, to measure intra-rater reliability.

Table 2: Traffic conflicts recording variables

Road users	
Type	Pedestrian, conventional bicycles, e-bikes
Age	Juvenile (<15), young (<40), middle-aged (<60), old
Gender	Male, female
Conflict indicators	
TTC	0-0.5 s, 0.5 s-1 s, 1 s-1.5 s, 1.5 s-2 s, >2 s
PET	0-0.5 s, 0.5 s-1 s, >1 s
Type of conflict	
Conflict severity	Class 1-5
Combinations of road users	E-E, E-C, E-P, C-C, C-P
Conflict directions	Same direction (close to camera), same direction (away from the camera), opposite, crossing, pedestrian standing
Evasive actions	
Reaction situation	Reaction, no reaction
Control situation	Controlled, uncontrolled (The behavior is controlled or not is based on whether there is actions, such as, swaying, keeping balance assisted by foot, etc.)
Type	Swerving, decelerating, accelerating, decelerating and swerving, decelerating before serving, swerving before decelerating, back up
Swerving direction	One swerves at left, one swerves at right, two swerve at left, two swerve at right, one left and one right

Note: P- pedestrian, C-conventional bicycle, E-electric bike.

2.2. Mixed logit model structure

A mixed logit model was used to fully account for unobserved heterogeneity in VRUs conflict severity analysis. The function is expressed as:

$$S_{in} = \beta_i X_{in} + \varepsilon_{in} \tag{1}$$

Where S_{in} is the propensity function that conflict *n* suffers from severity *i*, *i*=0, 1, 2, 3, 4 represents five levels of conflict severity. The β_i is a vector of estimable parameters varying across conflict severity *i*, X_{in} is a vector of explanatory variables for individual conflict *n*, ε_{in} is a stochastic error. When the stochastic error term of the utility function obeys the extreme value distribution, the standard logit model is expressed as follows:

$$Pn(i) = \frac{\exp(\beta_i X_{in})}{\sum \exp(\beta_I X_{In})} \tag{2}$$

The traditional logit model assumes that all parameters are fixed, that is, the effect of various influencing factors on the severity of conflict is fixed for each conflict. However, the occurrence of conflict is an extremely complex process. It is impossible to include all the factors affecting the severity of conflict and the interactive impact of various factors on the severity of conflict in the model, so that the effect of various factors included in the model is not fixed in each conflict, That is, the heterogeneity of the impact of various factors on accident severity (also known as unobserved heterogeneity). In order to fully consider heterogeneity in the model, a random item is added to the variable parameters during modeling to reflect the random variability of the impact of this factor on the severity of conflict:

$$\beta_{in} = \beta_i + \Gamma_i v_{in} \tag{3}$$

$$P(\beta_i) = \Gamma_i \Gamma_i^T \tag{4}$$

Where β_{in} , Γ_i is a parameter matrix what representing the covariance and potential correlation between random parameters, that is, the interaction of influencing factors on conflict severity *i*. v_{in} is the random term with the mean value of 0 and the covariance matrix as the unit matrix, which follows the standard multivariate normal distribution to characterize the unobserved heterogeneity; $P(\beta_i)$ represents the covariance matrix between random parameters. The model with the parameters of the traditional logit model set as random parameters is called the random parameter logit model, and its probability density function is shown in the formula(5).

$$P_n(i \mid v_{in}) = \int \frac{\exp(\beta_i X_{in})}{\sum \exp(\beta_I X_{In})} f(\beta_i \mid v_{in}) \mathrm{d}v_{in} \tag{5}$$

2.3. Data description

Three shared space in Shenzhen city was selected for this study and shown in Fig. 1. 7:30–9:30 and 17:30–19:30 were the morning and evening peak periods, that is, the periods when traffic conflicts are most likely to occur. The video recordings of these two 2-h periods at the three shard space were obtained. The frame rate of the video was 25 frames per second. The video resolution was 1920 × 1080 pixels.

(a) (b) (c)

Figure 1. Layout of the observed locations: (a) Lianxin Street; (b) Caitian Street; (c) Huanggang Street.

A total of 4426 road users were observed, and approximately 15 % of these road users (674 road users) were involved in a conflict. Specifically, 163 conflicts on Lianxin Street, 137 conflicts on Caitian Street, and 35 conflicts on Huanggang Street were recored. Traffic volume was counted by humans and a 15 min counting interval was used. The traffic volume of pedestrians, conventional bicycles and e-bikes were counted, respectively. All the variables consided in the logit model are shown in Table 3.

Table 3: Descriptive statistics for variables

Discrete variable		Number	Proportion(%)
Type of road users	Pedestrians	226	33.53
	Conventional bicycles	136	20.18
	e-bikes	312	46.29
Gender	Male	459	68.10
	Female	215	31.90
Age	Juvenile	18	2.67
	Young	435	64.54
	Middle-aged	192	28.49
	Old	29	4.30
Type of conflicts	Same direction	144	21.36
	Opposite direction	145	21.52
	Crossing	35	5.19
	Pedestrian standing	13	1.93
Continuous variable	**Mean**	**Standard deviation**	**Maximum**
The speed of road user 1	4.24	1.43	7.7
The speed of road user 2	2.17	1.59	7.25
Traffic volume of conventional bicycles	7.42	3.87	88.0
Traffic volume of e-bikes	20.24	23.90	156.0
Traffic volume of pedestrians	35.57	37.91	16.0

In addition, more than 2000 traffic crash data points from April 2013 to September 2019 were collected. Then, 35 crash data points occurred in shared space were screened out, as supplementary evidence for this study.

3. Analysis and Results

The mixed logit model is established using the conflict data. A total of 11 factors which have significant impacts on the traffic conflict severity are identified, under the 90% confidence level. The estimation results of model parameters are shown in Table 4. The mixed logit model identifies the parameters of two variables: traffic volume of e-bikes and traffic volume of pedestrians as random parameters. The results show that the female, traffic volume of e-bikes, traffic volume of pedestrians and conflict directions have a significant impact on level 1 conflict. The juvenile have a significant impact on level 4 conflict. The traffic volume of e-bikes and traffic volume of pedestrians have a significant impact on level 5 conflict.

Table 4: The estimation results of model parameters

conflict severity	Variable	Parameter estimate	Std. err	p-value
Class 1	Constant term	5.429	1.20	0.000
	female	0.812	0.49	0.097
	Traffic volume of e-bikes	0.112	0.06	0.077
	Traffic volume of pedestrians	0.074	0.03	0.031
	Conflict directions	1.709	0.92	0.064
Class 2	Constant term	2.628	0.51	0.000
Class 3	Constant term	2.037	0.51	0.000
Class 4	Constant term	1.387	0.54	0.010
	Juvenile	1.965	0.56	0.000
Class 5	traffic volume of e-bike	0.0185	0.01	0.030
	Traffic volume of pedestrians	0.0110	0.01	0.065

4. Discussion

According to the calculation results of the model, female, age, traffic volume of e-bikes and traffic volume of pedestrians are significant factors affecting the severity of conflict. The analysis results show the traffic volume of e-bike is significant variable for minor conflicts such as class 1 conflict and serious conflicts such as class 5 conflict, which have a great impact on the overall traffic safety level of shared space. At the same time, e-bikes are widely used in China and have a great influence. Therefore, the impact of e-bikes on VRUs conflicts at shared space will be analyzed and discussed in detail in this study.

4.1 E-bikes are more likely to get involved in conflicts than conventional bicycles

The conflict proportion is defined as the ratio of number of conflict participants to traffic volume. The conflict proportion for different road user types was calculated and shown in table 5. The comparison of conflict proportion between e-bikes and conventional bicycles is clearly shown in Fig. 2. The results show that the conflict proportion of e-bikes is much higher than that of conventional bicycles in the three observation locations. The conflict proportion of electric vehicles is even as high as 51.5% in Lianxin Road. This means that more than half of the e-bikes passing through the locations during the observation period have been involved in conflicts. Other studies have also proved that e-bikes are more likely to rise conflict and crash due to their higher speeds and accelerations [17, 18].

Table 5: The proportions of conflict participants for different road user types

	Location								
	Lianxin Street			Caitian Street			Huanggang Street		
	E	C	P	E	C	P	E	C	P
Traffic volume	367	1007	152	372	445	1475	191	296	121
Number of conflict participants	189	58	83	91	64	119	32	14	24
The proportion of conflict participants (%)	51.5	5.8	54.6	24.5	14.4	8.1	16.8	4.7	19.8

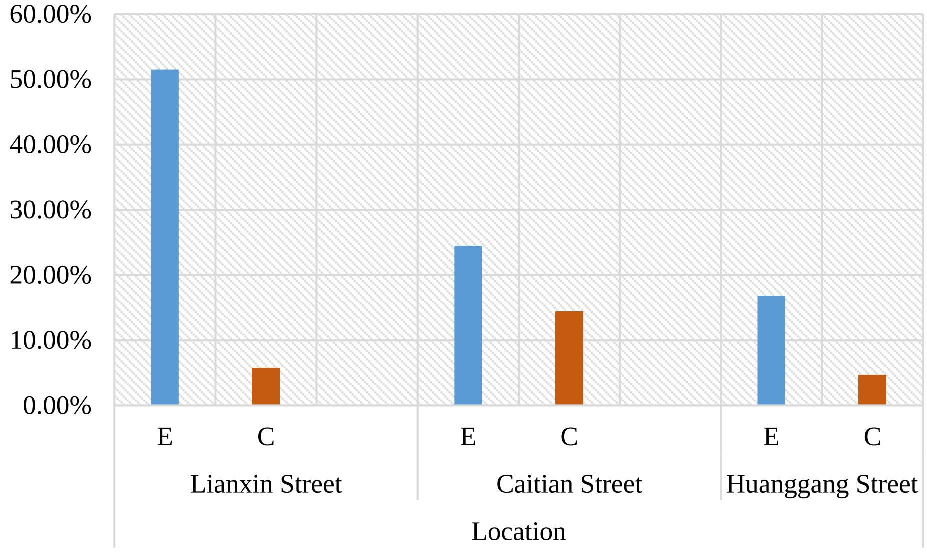

Figure 2: the comparison of conflict proportion between e-bikes and conventional bicycles.

4.2 Pedestrians are mainly affected in e-bike conflicts

Taking different combinations of road users as the conflict type division method, the results are shown in Table 6. The results are consistent with the above analysis, which still reflects the high risk of e-bikes at shared space, and pedestrians are likely to be the biggest victims of this high risk. The conflict between e-bikes and pedestrians is much higher than that between other road users.

Table 6: conflict numbers of different combinations of road users

Location	Total	E-E (%)	E-B (%)	E-P (%)	B-B (%)	B-P (%)
Lianxin Street	165	29.7	17.0	38.2	3.0	12.1
Caitian Street	137	4.4	5.1	52.6	3.6	34.3
Huanggang Street	35	14.3	14.3	48.6	2.9	20.0

4.3 e-bikes take more responsibility in shared space crashes

The 33 crashes happened in shared space during April 2013 to September 2019 are shown in table 7. In terms of crashes volume, crashes among VRUs in shared space are not as severe as motor vehicle crashes. But it can not be ignored that there are still a large number of property loss crashes data or minor injury crashes among pedestrians, conventional bicycles and e-bikes, which have not been recorded in the traffic police department. The traffic conflicts that easily lead to collisions frequently occur every day. Therefore, the traffic safety and travel comfort of shared space are still very serious. Table 7 shows that 23 of the 33 crashes involved e-bikes. Except for one unrecorded accident, e-bikes have assumed a certain degree of accident responsibility in the other 22 accidents, including 20 fully responsible accidents. This further confirms the conclusion of high risk of e-bike in the above analysis. On the other hand, the high-risk e-bike users are mainly men and young people.

Table 7: Crashes involving e-bikes

Crashes involving e-bikes(N=23)	
Traffic accident responsibility	There are 20 cases of full responsibility, 1 case of equal responsibility, 1 case of secondary responsibility and 1 case of no record.
Gender	There are 17 cases of male, 5 casesof female, and 1 case of not recorded.
Age	There are 0 cases of Juvenile, 17 cases of young, 5 cases of middle-aged, 0 cases of old,and 1 case of not recorded.

5. Conclusions

This study investigated the influence factor of traffic conflicts happening at shared space, and the conflict characteristics of e-bikes are analyzed in detail. A total of 12 h of video were collected at three observed locations. 4426 road users and 335 conflicts were observed. A mixed logit model was developed to fully account for unobserved heterogeneity. The results shows that the gender, age, traffic volume of pedestrian, traffic volume of e-bikes are the significant influencing factors of VRUs conflicts. The traffic volume of e-bike is significant variable for minor conflicts such as class 1 conflict and serious conflicts such as class 5 conflict. Further analysis found that e-bikes are more likely to get involved in conflicts than conventional bicycles. Pedestrians are mainly affected in e-bike conflicts. In addition, the crashes data shows that e-bikes are often the ones who are responsible for the accident. This highlights that e-bikes is the significant variable of VURs conflict in shared space, and it is high risk in shared space. Speed limit and regulating the behavior of e-bikes may be effective measures to solve this problem.

Some methodological issues must be acknowledged. Althout the DOCTOR method is a standardized and applicable conflict identification method. This method requires a lot of manpower and time, which limits the amount of data. More automated conflict identification methods will be considered in the future.

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