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Article

Risk-taking behavior of electric cyclists and policy recommendations: A case study

Yanqun Yang[1,2], Heming Tian[1,2], Yang Feng[1,2], Said M. Easa[2,3], Xinyi Zheng[2,4,*]

[1] College of Civil Engineering, Fuzhou University, Fuzhou 350116, China
[2] Joint International Research Laboratory on Traffic Psychology & Behaviors, Fuzhou University, Fuzhou 350116, China
[3] Department of Civil Engineering, Toronto Metropolitan University, Toronto, ON M5B 2K3, Canada
[4] School of Humanities and Social Sciences, Fuzhou University, Fuzhou 350116, China
*** Corresponding author:** Xinyi Zheng, zhengxinyi@fzu.edu.cn

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Abstract: With the rapid increase in electric bicycle (e-bikes) use, the rate of associated traffic accidents has also escalated. Prior studies have extensively examined e-bike riders' injury risks, yet there is a limited understanding of how their behavior contributes to these accidents. This study aims to explore the relationship between e-bike riders' risk-taking behaviors and the incidence of traffic accidents, and to propose targeted safety measures based on these insights. Utilizing a mixed-methods approach, this research integrates quantitative data from traffic accident reports and qualitative observations from naturalistic studies. The study employs a binary logistic regression model to analyze risk factors and uses observational data to substantiate the model findings. The analysis reveals that assertive driving behaviors among e-bike riders, such as running red lights and speeding, significantly contribute to the high rate of accidents. Moreover, the lack of protective gear and inadequate safety training are identified as critical factors increasing the risk of severe injuries. The study concludes that comprehensive policy interventions, including stricter enforcement of traffic laws and mandatory safety training for e-bike riders, are essential to mitigate the risks associated with e-bike use. The findings advocate for an integrated approach to urban traffic management that enhances the safety of all road users, particularly vulnerable e-bike riders.

Keywords: e-bikes; epidemiological studies; natural observation; risk-taking behavior; logit model; riding safety

1. Introduction

E-bikes have become a popular means of travel worldwide. According to statistics, the number of e-bikes worldwide has exceeded 300 million (E-bicycles, 2021). However, the rise in their popularity has been accompanied by increased related traffic incidents, highlighting significant safety concerns. Previous research has extensively documented the vulnerability of electric cyclists to severe injuries. Yet, a critical gap remains in understanding the interplay between the intrinsic injury risks associated with electric two-wheeler usage and the prevalence of risk-taking behaviors among their riders.

This study aims to bridge this gap by providing a comprehensive analysis of the factors contributing to the high incidence of injuries among e-bike riders and their propensity for engaging in risky behaviors. Despite the wealth of epidemiological data on traffic injuries, few studies have systematically explored how the unique characteristics of e-bikes influence rider behavior and safety outcomes. Our research addresses this oversight by integrating injury data analysis with behavioral observations, thereby offering a dual perspective largely overlooked in the literature.

To address the complexities of e-bike-related injuries and behaviors, this paper is structured as follows: Section 1 provides a detailed review of the literature, underscoring the known risks and examining the existing measures to mitigate these risks. Section 2 introduces the methodology employed in this study, including the observational techniques and analytical frameworks used to gather and analyze data. Section 3 presents our findings, which reveal critical insights into the correlation between e-bike design features, rider behaviors, and injury outcomes. Based on these insights, Section 4 discusses policy recommendations tailored to enhance the safety of e-bike riders, proposing both regulatory changes and community-awareness initiatives.

Through this approach, our study contributes significantly to the existing body of knowledge by elucidating the factors that increase the susceptibility of e-bike riders to accidents and by offering grounded, practical solutions for policymakers and urban planners. By aligning our investigative focus with policy-oriented outcomes, we aim to foster safer urban mobility landscapes for all road users, particularly those adopting this increasingly prevalent mode of transportation.The research process of this study is shown in **Figure 1**.

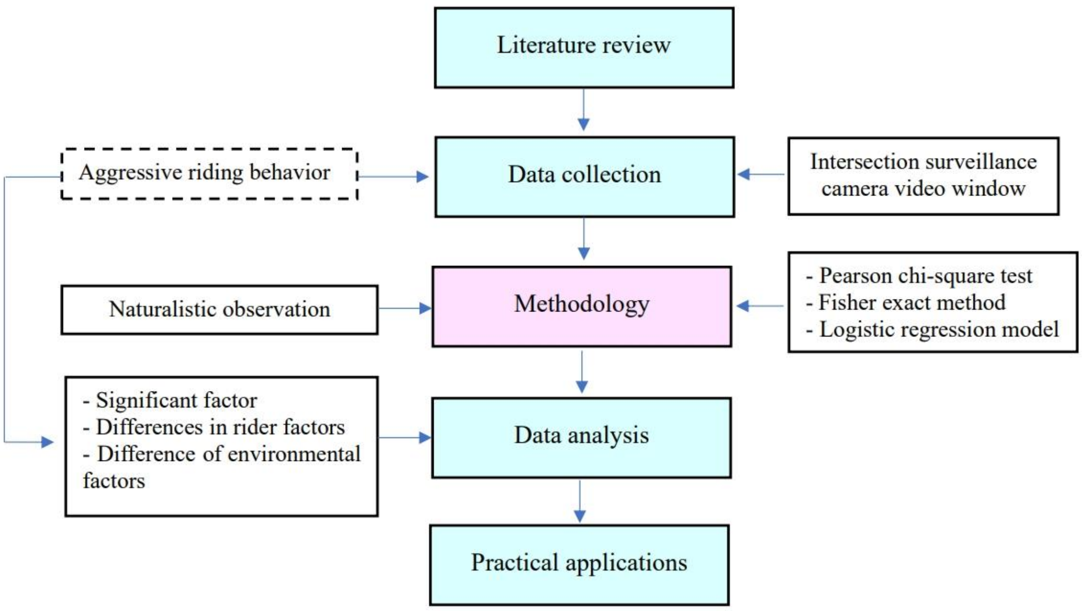

Figure 1. Study tasks.

2. Literature review

Due to the frequent traffic accidents related to e-bikes, there have been increasing numbers of epidemiological studies on road accidents, and the results related to e-bikes have obvious tendencies. Almost all studies have pointed out that e-bike riders are very prone to serious injuries or even deaths when road traffic accidents occur.

After literature retrieval, this study screened the obtained literature, which was independently conducted by a master's student majoring in traffic engineering. It made a descriptive analysis of the included literature after eliminating the repeated publications, incomplete information, obvious design defects, and statistical calculation. However, accident data from police and hospital sources are casualty exclusive. Therefore, the classification of injury severity is often more biased towards severe injuries and fatal injuries. Since e-bikes are commonly classified as a type of non-motorized vehicle, they share similar characteristics with other non-motorized vehicles in terms of lacking protective measures for riders. Therefore, to highlight their propensity to cause riders' injuries, this study references and incorporates epidemiological research on traffic injuries related to non-motorized vehicles.

Miao (2007) put forward in his research. Because of the poor protection and stability of non-motorized vehicles, non-motorized vehicle riders are vulnerable to serious injuries after accidents with motor vehicles. After analyzing the clinical data of all patients with traumatic brain injury admitted to the Department of Neurosurgery, General Hospital of Tianjin Medical University from January 2011 to December 2016, Wang (2017) found that the number of patients injured by traffic accidents ranked first, among which non-motorized vehicle injuries accounted for 59.34% of all patients hospitalized due to traffic injuries, and although the mileage of e-bikes was much shorter than that of motor vehicles, vehicle-bike injuries became the second cause of injury.

Cai et al. (2008) and others found that among the 1071 patients with traffic injuries in a hospital in Lishui, one-third were injured by bicycles, electric bicycles, and motorcycles, with 7 deaths, including 5 deaths related to e-bikes. At the same time, with the popularity of e-bikes in recent years, there are more and more injuries and deaths related to e-bikes. Lu et al. (2021) retrospectively analyzed the case data of road traffic injuries reported by Suzhou Emergency Center and disposed on site from January 2017 to December 2019. They found that the patients with electric bicycle traffic injuries accounted for 52.3% of all traffic injuries, and the number of injured parts of the patients with electric bicycle traffic injuries was significantly higher than that of other traffic injuries. After analysis, the study found that the proportion of serious injuries in patients with electric bicycle traffic injuries was significantly higher than in patients with other traffic injuries. Among 1516 patients who died at the scene, there were 1070 patients with electric bicycle traffic injuries, accounting for 70.6%, which was significantly higher than that in patients with other traffic injuries. Zhang et al. (2020) made a retrospective analysis of road traffic injuries in Suzhou in 2020 and found that 112 patients died at the scene in pre-hospital emergency treatment, 91.1% of whom included head and neck injuries. According to different travel modes, 51 cases (45.54%) died of e-bikes, which was much higher than 27 cases (24.11%) who died of walking and 25 cases (22.32%) who died of motor vehicles.

In the epidemiological study of road traffic injuries, many studies have compared the injury degree of e-bike drivers and the injury degree of motor vehicle drivers or passengers after a collision between motor vehicles and e-bikes. It is pointed out that e-bike drivers are more vulnerable to severe injuries when involved in traffic accidents because of the lack of relevant safety protection.

Wang et al. (2014) retrospectively analyzed 338 cases of electric bicycle traffic injuries admitted to Lishui People's Hospital from January 2010 to December 2012. Among 97 cases, 6 cases died, with a death percentage of 6.2%, and 26 cases were disabled, with a disability percentage of 28.8%, which was much higher than the death percentage of 0.4% and the disability percentage of 1.2% in non-motorized vehicle collision injuries. It shows the seriousness of the consequences of e-bikes colliding with motor vehicles. Li et al. (2022) analyzed 1619 cases of e-bike injuries admitted to the emergency department of People's Hospital of Guangxi Zhuang Autonomous Region. The results showed that compared with the collision between e-bikes and e-bikes, the collision between e-bikes and motor vehicles often had more serious consequences. In the case of similar accident rates between e-bikes and e-bikes (37.37% and 33.91%), In the accidents with serious injuries, the proportion of e-bikes colliding with motor vehicles is 67.50%, and in the accidents with serious injuries, the proportion of e-bikes colliding with motor vehicles is 61.97%, both higher than that of e-bikes colliding with e-bikes (20.83% and 20.09%).

The "vulnerable road user" nature of e-bike riders (Blaizot et al., 2013) and the rider's aberrant riding behaviors (Wang et al., 2021) have brought more traffic safety problems and made road traffic management more difficult. The existing laws and regulations lack strong constraints on the riding behavior of e-bike riders, the riders' legal awareness is weak, and they do not obey the relevant traffic rules, which makes traffic accidents frequent. In China, the number of e-bike accidents in 2019 nearly doubled compared to 2017 (NBS, 2021). In accidents related to e-bikes, riders of e-bikes are more vulnerable to severe injuries due to lack of protection. Therefore, more and more researchers have begun to pay attention to the severe consequences of traffic accidents in e-bikes (Yang et al., 2015). The research data show that in road traffic accidents, e-bike riders have a higher injury probability and a significantly higher mortality rate than other reasons (Zeng, 2006). At the same time, in the case of a collision between an e-bike rider and a motor vehicle driver, the riders of the e-bike have a higher probability of serious injury or even death about 37.5% compared with the passengers and drivers of the motor vehicle (Liu et al., 2012). The frequent accidents of e-bikes are closely related to the assertive riding behavior of e-bike riders. Its light and flexible driving characteristics and the protection of vulnerable groups by traffic police after accidents have led to such behavior of e-bike riders.

Related research generally believes that the reason for frequent traffic accidents of e-bikes is that e-bike drivers are more likely to have traffic accidents because they violate traffic rules (Yang et al., 2015). Chen (2022) and others found that 73.65% of the electric bicycle riders who were injured by road traffic in Songjiang District of Shanghai from June 2020 to May 2021 did not know the speed limit of 25 km/h, 44.91% of them had ever run a red light, 73.05% of them had ever ridden at a speed of ≥ 30 km/h, and at the same time, they rode with one hand, carried passengers The frequency of incorrect use of turn signals when cornering is also high. In another study involving young e-bikers in the emergency data of hospitals in Shanghai, it is shown that "using a mobile phone," "turning" and "suddenly changing driving mode" are the key factors affecting the riding safety of e-bikes (Ren, 2020). In addition, the characteristics of e-bikes have also caused frequent accidents. E-bikes have the characteristics of high speed, flexible driving, poor driving stability, poor protection, and poor braking performance, and these characteristics have caused the braking system to fail to ensure safe braking in case of emergency or danger, which has led to the occurrence of e-bike traffic accidents (Chen, 2013).

After a traffic accident, the e-bike driver is the weak side in the traditional view, and the traffic police should take the principle of being people-oriented in paying compensation without responsibility, so they can only protect the e-bike side when dealing with traffic disputes between motor vehicles and non-motorized vehicles (Wu, 2010). The result of not severe punishment further increases the possibility of strong driving behavior of e-bike riders to a certain extent, which further makes traffic accidents related to e-bikes more frequent.

At present, there is literature on the application of natural observation in the riding behavior of e-bikes. Hua et al. (2003) studied the illegal behavior of e-bike riders in Suzhou in December 2021 by non-participatory observation. The results showed that among the 83,647 riders during the on-site observation period, the number of people who did not wear safety helmets correctly or did not wear safety helmets ran red lights and illegally carried people was 20,579, 9534 and 3991 respectively, with the incidence rates of 24.60% and 3991 respectively. Lin (2021) observed a total of 14,144 private e-bikers and 20,410 shared e-bikers at six intersections with the largest traffic flow and people flow in Shantou city. After analyzing the obtained data, it was concluded that the common illegal behaviors of e-bikers in Shantou City and the influence of traffic police enforcement at intersections on the illegal behaviors of e-bikers prepared a data basis for providing corresponding measures in the future. Wu et al. (2012). observed 451 two-wheeled bikers (222 e-bike and 229 bicycle riders) waiting for red lights at three intersections in Beijing, and then conducted research and analysis on their behavior of waiting for red lights, providing valuable insights for understanding the behavior of two-wheeled vehicles running red lights, and discussing its significance for improving road safety.

3. Data collection

This paper analyzes the causes of different types of non-motorized vehicle risky behaviors based on the advantages of natural observation to compare the riding behaviors of bicycle riders (B), electric bicycle riders (EB), and electric moped riders (EM) at signalized intersections.

3.1. Observation sites

The traffic behavior of road users is investigated by video survey. To avoid the influence of the camera on the riding behavior of non-motorized vehicle drivers and ensure the shooting range of the camera, the method of collecting traffic police monitoring and observes the non-motorized vehicle riders in the field of vision from the perspective of the monitoring camera with a single viewport. **Figure 2** shows the observation perspective. To ensure the smooth development of the study and the representativeness of the data, the observation sections selected in this study all meet the following characteristics: the sections are typical sections of urban roads or suburban roads and have a large amount of e-bike traffic. After screening and comprehensive consideration of previous studies, this study has selected four intersections and four sections in Fuzhou for observation and research. The distribution of observation sites is shown in **Figure 3**, and the feature table is shown in **Table 1**.

(a) Intersection **(b)** Section

Figure 2. Observation angle of monitoring video.

Figure 3. Distribution of observation sites.

Table 1. Characteristics of observation sites.

Name	Mark in the picture	Type	Location	Physical separation of non-motorized vehicle lanes	Import and export road
Jiangsu Road-Bincheng Avenue Intersection	Triangle-1	Crossings	Suburbs	Without	3 in and 2 out
Jianping Road-Qishan Avenue Intersection	Triangle-2	Crossings	Suburbs	With	5 in and 3 out from north and south East 4 in 3 out West 3 in 3 out
Wusi Road Hualin Road Intersection	Triangle-3	Crossings	Urban district	With	4 in and 2 out
Guping Road Hudong Road Intersection	Triangle-4	Crossings	Urban district	Without	3 in and 2 out
Bincheng Avenue Section	Circle-1	Section	Suburbs	Without	-[a]
Qishan Avenue Section	Circle-2	Section	Suburbs	With	-[a]
Wusi Road Section	Circle-3	Section	Urban district	With	-[a]
Guping Road Section	Circle-4	Section	Urban district	Without	-[a]

[a] Not applicable.

3.2. Study period

The survey date is from 11 March to 10 April. During this period, the weather of sunny and rainy days is included in each survey location, so two days are selected. The survey period is from 7:30 to 8:00 in the morning peak, from 12:00 to 12:30 in the flat peak, and from 5:30 to 5:30 p.m. peak. A total of 3 hours of monitoring video was observed at each observation site, and the total observation time was 24 h.

3.3. Collected data

All monitoring data were recorded and processed by 15 graduate students majoring in transportation. The data recorded the location, period, service level of non-motorized vehicle lanes, suburbs, weather, whether there was a traffic controller, date, temperature of the day, whether it was a delivery clerk, whether there was a physically separated non-motorized vehicle lane, gender, age, vehicle type Information about whether or not there are risky behaviors and types of risky behaviors, which are recorded in excel files. The recording standard is shown in **Table 2**. To ensure the quality of the data obtained, all personnel have received training on the identification of different types of e-bikes, identification of different behaviors of bikers, and data quality control, the final data were reviewed by three experts in the field of traffic engineering.

Table 2. Example of collected behavior data.

Information	Example
Name	Wusi Road Hualin Road Intersection
Time	Peak
Location	City proper
Weather	Rain
Traffic controller	With

Table 2. (*Continued*).

Information	Example
Delivery man	No
Non-motorized vehicle lanes	With
Gender	Male
Age	Over 35 years old
Non-motorized vehicle type	Electric moped
Risky behavior	Run the red light

4. Methodology

4.1. Pearson chi-square test

The Pearson chi-square test is usually used to test categorical variables. The original hypothesis (H_0) in the test is that the distribution of the number of events that have occurred in a sample will follow a specific theoretical distribution. The test can also be used to test fitness and independence. In this study, the Pearson chi-square test was used to study whether various factors of non-motorized cyclists have a significant impact on whether non-motorized cyclists take risk behaviors.

In the independence test, it is first necessary to build a contingency table of r rows and c columns. Under the assumption of independent events, the expected number of times for each field is:

$$E_{i,\,j}=\frac{(\sum_{nc=1}^{c}O_{i,\,nc})\cdot(\sum_{nr=1}^{r}O_{nr,\,j})}{N} \tag{1}$$

where, N is the sample size, $O_{i,\,nc}$ and $O_{nr,\,j}$ is the frequency of observation, and $E_{i,\,j}$ is the expected frequency. Then, x^2 is given by:

$$\chi^2=\sum_{i=1}^{r}\sum_{j=1}^{c}\frac{(O_{i,\,j}-E_{i,\,j})^2}{E_{i,\,j}} \tag{2}$$

The DF in the Pearson Chi-square test is calculated based on the number of cells in the contingency table that can be freely valued.

4.2. Binomial logit model

The binomial logit model is a statistical method used to predict the probability of a binary outcome based on one or more predictor variables. In this study, the binomial logit model is used to analyze the influencing factors of non-motorized vehicle risk-taking behavior.

If the parameter μ, β have Gumbel distribution Gumbel (μ, β), then the probability density function is given by,

$$f(x;\mu,\beta)=\frac{1}{\beta}e^{-z-e^{-z}},\ z=\frac{x-\mu}{\beta} \tag{3}$$

where μ is the location coefficient (mode) of the Gumbel distribution and β is its scale coefficient, which determines the distribution's dispersion degree. When μ = 0 and β = 1, the Gumbel distribution corresponds to the standard Gumbel distribution. The probability distribution of Gumbel (0, 1) is given by,

$$f(x) = e^{-x} e^{-e^{-x}} \tag{4}$$

In the utility maximization theory, the probability of decision maker *n* selecting Option *i* is given by,

$$P_n(i) = p(\varepsilon_{jn} - \varepsilon_{in} < V_{in} - V_{jn}) \tag{5}$$

where ε_{in} and ε_{jn} are random utility, V_{in} and V_{jn} are representative observed determination terms. In the binomial logit model, the random utility part ε_{in} and ε_{jn} are subject to Gumbel (0, 1) distribution and ε_{in}, ε_{jn} are independent. Then, $\varepsilon_{in} - \varepsilon_{jn}$ obey the standard Logistic distribution with parameters 0 and 1,

$$P_n(i) = P(\varepsilon_{jn} - \varepsilon_{in} < V_{in} - V_{jn}) = F(V_{in} - V_{jn}) = \frac{1}{1 + e^{-(V_{in} - V_{jn})}} \tag{6}$$

$$P_n(i) = \frac{e^{V_{in}}}{e^{V_{in}} + e^{V_{jn}}} \tag{7}$$

The deterministic part of utility can be expressed as a linear combination of multiple independent variables, namely,

$$V_{in} = \beta' X_{in}, V_{jn} = \beta' X_{jn} \tag{8}$$

Finally, in the binomial logit model, the probability of decision maker *n* choosing Option *i* is,

$$P_n(i) = \frac{e^{\beta' X_{in}}}{e^{\beta' X_{in}} + e^{\beta' X_{jn}}} \tag{9}$$

In this study, the order $Y = 1$ means that non-motorized cyclists have taken risky riding behavior, $Y = 0$ indicates that the non-motorized cyclist has not taken any risky riding behavior. Let the probability of non-motorized cyclists taking risky riding behavior $P(Y = 1) = p1$ and the probability of non-motorized cyclists not taking risky actions is $P(Y = 0) = p0 = 1 - p1$. Then, by definition, the odds of success (Odds) of non-motorized cyclists taking risky riding behavior are given by,

$$Odds = \frac{p_1}{1 - p_1} = \frac{p_1}{P_0} \tag{10}$$

5. Analysis and results

5.1. Adventure behavior

Through video observations, the traffic behavior data of 18,236 non-motorized cyclists passing through the signal intersection was extracted. After the data containing unknown information was extracted, the traffic behavior data of 16,243 non-motorized cyclists passing through the signal intersection was obtained, including 4362 electric bicycle riders, 11,775 electric moped riders, and 106 bicycle riders. Observations at signal intersections reveal potential risky behaviors by cyclists, including not wearing safety helmets, using mobile phones, answering and making calls, riding with one hand, riding with one hand, umbrella with one hand, carrying a large number of goods, carrying people in violation of regulations, parallel traffic on the road, sudden braking, running red lights, going backward, driving on the sidewalk, speeding The distance between vehicles is too close, the vehicle flow is inserted, the pedestrian crossing is not passed, the vehicle is overtaken illegally and the canopy is installed.

5.2. Incidence rate of risk-taking behavior

The incidence of adventure behaviors of B, EB, and EM is shown in **Figure 4**. When non-motorized cyclists pass through the signal intersection, 67.70% of electric bicycle riders (EB) and 74.47% of electric moped riders (EM) will take risk behaviors, which is 2.47 times and 2.72 times of the bicycle riders (B)who take risk behaviors in percentage. Pearson chi-square test and multiple comparison method are used to analyze the difference in the incidence of adventure behaviors of EB, EM, and B. When the sample size is less than 5, the Fisher exact test is used to modify the Pearson chi-square test results, and the results are shown in **Table 3**. At a 95% confidence level, there is a significant difference in the proportion of risk-taking behavior among electric bicycle riders, electric moped riders, and traditional bicycle riders. The highest proportion of adventurous behavior is taken by EM, followed by EB, and the lowest proportion of adventurous behavior is taken by cyclists.

Figure 4. Incidence of adventure behavior of EB, EM, and B.

Table 3. Incidence of adventure behavior of EB, EM, and B.

Types Of Risk-Taking Behavior	Non-Motorized Vehicle Type			*P* Value Between Three Groups	Chi-square statistic[a]
	EB	EM	B		
Not Wearing A Safety Helmet	57.96%	63.90%	15.09%	<0.001	147.94
Retrograde Riding	11.46%	6.87%	4.72%	<0.001	91.91
Insert Into Other Lanes	10.98%	10.92%	8.49%	0.719	0.66
Run The Red Light	5.48%	7.85%	1.89%	<0.001	31.46
Ride With One Hand	0.99%	1.42%	0.94%	0.093	4.75

[a] DF = 2.

The main risky behavior of cyclists is not wearing safety helmets. The proportion of electric bicycle riders and electric moped riders who do not wear safety helmets is 57.96% and 63.90%, respectively, which is significantly higher than that of traditional bicycle riders who do not wear safety helmets (15.09%). The reverse rate of EB is the highest, followed by EM, and the reverse rate of cyclists is the lowest. The proportion of electric bicycle riders, electric moped riders, and traditional bicycle riders inserting into other lanes when crossing intersections is 10.98%, 10.92%, and 8.49% respectively. At a 95% confidence level, the proportion of electric bicycle riders, electric moped riders, and bicycle riders inserting into other lanes when crossing intersections is not significantly different, However, from a percentage point of view, EB and EM are more likely to insert into other lanes when crossing intersections. The red-light running rate of electric bicycle riders, electric moped riders, and traditional bicycle riders is 5.48%, 7.85%, and 1.89% respectively. Under 95% confidence, the red-light running rate of electric moped riders is significantly higher than that of electric bicycle and traditional bicycle riders, The red-light running rate of electric bicycle riders is 2.90 times that of bicycle riders. The proportions of electric bicycle riders, electric moped riders, and traditional bicycle riders riding with one hand were 0.99%, 1.42%, and 0.94% respectively, and there was no significant difference among the three at 95% confidence level.

5.3. Incidence rate of risk-taking behavior of male and female

Table 4 shows the difference in the incidence of risk-taking behavior between males and females of non-motorized cyclists. The incidence of risky behaviors of male and female cyclists was 77.81% and 62.60%, respectively. Under a 95% confidence level, male cyclists' risky behaviors were significantly higher than that of female cyclists. At a 95% confidence level, the incidence of risky behaviors of male electric bicycle riders, male electric moped riders, and male traditional bicycle riders is significantly higher than that of female cyclists. In terms of percentage, the incidence of risky behaviors of cyclists is considerably lower than that of EB and EM.

Table 4. Incidence of adventure behavior of male and female cyclists.

Non-motorized Vehicle Type	Gender		***P*-value**	**Chi-square statistic[a]**
	Male	**Female**		
All	77.81%	62.60%	<0.001	430.98
Electric Bicycle	75.05%	60.22%	<0.001	108.95
Electric Moped	78.89%	64.54%	<0.001	269.47
Bicycle	38.57%	5.56%	<0.001	11.43

[a] DF = 1.

5.4. Risk-taking behavior of cyclists under and over 35 years

The incidence of risky behaviors of cyclists of different ages is shown in **Table 5**. The incidence of risky behaviors of cyclists under 35 years old was 71.56%, and that of cyclists over 35 years old was 73.49%. Under 95% confidence, the incidence of risky behaviors of cyclists over 35 years old was significantly higher than that of cyclists under 35. The same result is also reflected in the electric bicycle group. Under a 95% confidence level, the incidence of risky behaviors of EM riders under 35 years old is significantly higher than that of EM riders over 35 years old. At 95% confidence level, there is no significant relationship between whether cyclists have risky behaviors and the age of cyclists. To avoid the impact of a small sample size on the analysis results, we used Fisher's exact test. The results were consistent with those obtained from the Pearson Chi-square test. However, the incidence of risky behaviors of cyclists is significantly lower than that of EB and EM.

Table 5. Incidence rate of risk-taking behavior of cyclists aged over 35 and under 35.

Non-motorized Vehicle Type	Age		*P* Value	Chi-square statistic[a]
	Under 35 years old	Over 35 years old		
All	71.56%	73.49%	0.006	7.65
Electric Bicycle	67.78%	74.29%	<0.001	21.08
Electric Moped	75.26%	73.43%	0.020	5.42
Bicycles	28.57%	22.72%	0.780	0.078

[a] DF = 1.

5.5. Factors influencing cyclist's risk-taking behavior

Many factors affect non-motorized vehicle riders' decision to take risky behavior when arriving at the signal intersection. This study uses the binomial logit model to study the driving behavior of non-motorized vehicle riders and analyze the influencing factors. **Table 6** shows the descriptive characteristics of the candidate influencing factors for cyclists to take risks.

Table 6. Descriptive characteristics of candidate variables.

Variable		Variable Characteristics	Frequency (Percentage)
Gender	Male	EB: 2220, EM: 8140, B: 70.	10,430 (64.21%)
	Female	EB: 2142, EM: 3635, B: 36.	5816 (35.79%)
Age	Under 35 years old	EB: 2592, EM: 6743, B: 84.	9419 (57.99%)
	Over 35 years old	EB: 1770, EM: 5032, B: 22.	6824 (42.01%)
Non-motorized vehicle type		EB: 4362, EM: 11,775, B: 106.	16,243 (100%)
Traffic controller		With traffic controllers: 4222, Without traffic controllers: 12,021.	16,243 (100%)
Delivery man		It's a delivery man: 610. It's not a delivery man: 15,633.	16,243 (100%)
Non-motorized vehicle lanes		There are non-motorized vehicle lanes: 8312. There are no non-motorized vehicle lanes: 7931.	16,243 (100%)
Weather		Sunny day: 5695, Rainy day: 10,548	16,243 (100%)
Location		Suburb: 4780, The city proper: 11,463	16,243 (100%)
Time		Flat peak: 4715, Peak: 11,528	16,243 (100%)

The optimal solution of the binomial logit model for cyclists to take risks is shown in **Table 7**. The explanatory variables of the optimal solution are statistically significant at 95% confidence. The odds ratio of the binary variable "male" and "female" is 0.484, indicating that female non-motorized cyclists are 0.484 times more likely to take risky riding behaviors than male non-motorized cyclists. The odds ratio of the binary variable "under 35 years old" and "over 35 years old" was 1.209, indicating that non-motorized cyclists over 35 years old were 1.209 times more likely to take risky riding behaviors than non-motorized cyclists under 35 years old. Among the non-motorized vehicle type variables, the odds ratio of the variable "B" and the variable "EB" is 0.313; this means that the likelihood of bicyclists engaging in risky behaviors is 31.3% of that of electric bike riders. Similarly, the likelihood of EM riders engaging in risky behaviors is 140.3% of that of electric bike riders. The presence or absence of traffic controllers also significantly impacts whether non-motorized vehicle riders take risky riding behavior. The probability of non-motorized vehicle riders taking risky riding behavior with traffic controllers is 17.9% lower than without traffic controllers.

Table 7. The optimal solution of the binomial logit model for cyclists' risky behavior.

Variable		**OR**	**Standard Deviation**	***P* Value**	**Marginal Effect**
Gender	Male and Female	0.484	0.019	<0.001	−0.129
Age	Under 35 Years Old and Over 35 Years Old	1.209	0.048	<0.001	0.034
Non-Motorized Vehicle Type	B and EB	0.313	0.073	<0.001	−0.207
	EM and eB	1.403	0.060	<0.001	0.060
Traffic Controller	Without and with	0.821	0.038	<0.001	−0.035
Is it a delivery man	No, and yes	0.598	0.058	<0.001	−0.091
Non-motorized vehicle lanes	With and without	1.593	0.065	<0.001	0.083
Weather	Sunny Day and Rainy Day	1.385	0.057	<0.001	0.058
Location	Suburb and the city proper	2.734	0.112	<0.001	0.179
Time	Flat peak and Peak	0.751	0.035	<0.001	−0.050

* Note: In this table, the reference groups are Male, Under 35 Years Old, EB (Electric Bike), Without traffic controller, not a delivery man, Without a non-motorized vehicle lane, Sunny day, City proper, Flat peak for the variables.

Table 8. Optimal solution of the binomial logit model for cyclists' red light running behavior.

Variable		**OR**	**Standard Deviation**	***P* Value**	**Marginal Effect**
Gender	Male and Female	0.563	0.044	<0.001	−0.035
Age	Under 35 Years Old and Over 35 Years Old	0.643	0.047	<0.001	−0.027
Non-Motorized Vehicle Type	B and EB	0.232	0.172	0.048	−0.088
	EM and eB	1.299	0.104	0.001	0.016
Traffic Controller	With and without	0.364	0.039	<0.001	−0.061
Is it a delivery man	NO, and YES	8.919	0.871	<0.001	0.131
Machine-non-Separation	With and without	0.704	0.050	<0.001	−0.021
Weather	Sunny Rainy Days	1.157	0.078	0.030	0.009
Location	Suburb and the city proper	3.050	0.279	<0.001	0.067
Time	Flat peak and Peak	0.715	0.050	<0.001	−0.020

* Note: In this table, the reference groups are Male, Under 35 Years Old, EB (Electric Bike), Without traffic controller, not a delivery man, Without a non-motorized vehicle lane, Sunny day, City proper, Flat peak for the variables.

Whether it is a delivery man or not also significantly impacts the risk-taking behavior of non-motorized vehicle riders. However, different from the previous research results, the probability of the risk-taking behavior of the delivery man is more than that of the non-delivery man. To explore the causes of this phenomenon, the logit model is also established by taking red light running and retrograde driving as dependent variables. The optimal solution of the binomial logit model for cyclists to run the red light and retrograde riding is shown in **Tables 8** and **9**. Under the condition that special non-motorized vehicle lanes are set up, non-motorized cyclists are more likely to have risky riding behaviors. In rainy weather, non-motorized cyclists are likelier to take risky riding behavior. Non-motorized cyclists are more likely to take risks in suburban areas and during flat peak periods.

Table 9. Optimal solution of the binomial logit model for cyclists' retrograde riding behavior.

Variable		OR	Standard Deviation	*P* Value	Marginal Effect
Gender	Male and Female	1.049	0.068	0.460	0.003
Age	Under 35 Years Old and Over 35 Years Old	1.445	0.098	<0.001	0.025
Non-Motorized Vehicle Type	B and EB	1.439	0.708	0.459	0.025
	EM and EB	0.705	0.047	<0.001	−0.024
Traffic Controller	With and without	0.008	0.004	<0.001	−0.333
Is it a delivery man	NO, and YES	2.286	0.290	<0.001	0.056
Machine-non-Separation	With and without	1.763	0.125	<0.001	0.039
Weather	Sunny and Rainy Days	1.121	0.073	0.080	0.001
Location	Suburb and the city proper	8.461	1.095	<0.001	0.145
Time	Flat peak and Peak	1.182	0.076	<0.001	0.011

* Note: In this table, the reference groups are Male, Under 35 Years Old, EB (Electric Bike), Without traffic controller, not a delivery man, Without a non-motorized vehicle lane, Sunny day, City proper, Flat peak for the variables.

For Logistic regression, the umber of obs = 16,243 and LR chi2(10) = 1765.55. Log likelihood = −8691.3096 (Prob > chi2 = 0.0000, Pseudo $R2$ = 0.0922).

When other variables are constant, the probability of female cyclists taking risky riding behavior is 12.9% lower than that of men, which may be caused by men's willingness to take risks than women. When other variables are constant, the probability of cyclists over 35 years old taking risks is 3.4% higher than that of cyclists under 35 years old, which is different from the conclusion that young people are more willing to take risks than being hurt in previous studies. In recent years, the propaganda of road traffic safety in China has been increasing, and schools, as the most common and concentrated place for road traffic safety education, will have a subtle influence on students' psychology. Young people know how to abide by road traffic safety laws better than middle-aged or elderly people. The probability of cyclists taking risks is 20.7% lower than that of EB, and the probability of EM taking risks is 6.0% higher than that of EB.

As mentioned earlier, EB and EM are more serious than bicycles after accidents as vehicles with faster speed, worse balance, and more difficult braking. However, the data analysis results of the natural observation method are realistic. Electric bikers are more likely to take risky riding behavior than cyclists. How to educate and restrain Electric bikers is a crucial link to reducing road traffic accidents. Traffic controllers also influence whether non-motorized cyclists will take risky driving behavior. The probability of non-motorized cyclists taking risky behavior at intersections with traffic controllers is 3.5% lower than that at intersections without traffic controllers, which is the same as the conclusion that cyclists often reduce their risky behavior because of fear of being punished in previous studies. The probability of non-motorized vehicle riders taking risks at intersections with special non-motorized vehicle lanes is 8.3% higher than that at intersections without special non-motorized vehicle lanes. Special non-motorized vehicle lanes will make non-motorized vehicle riders think that their surrounding environment is safer, thus making their riding behavior comfortable and growing. Non-motorized cyclists on rainy days are 5.8% more likely to take risks than those on sunny days. On rainy days, non-motorized cyclists will take some risks to shorten their exposure to bad weather.

For Logistic regression, the number of obs = 16,243 and LR chi2(10) = 1033.38. Log likelihood = −3675.2013 (Prob > chi2 = 0.0000, Pseudo *R*2 = 0.1233).

For Logistic regression, the number of obs = 16,243 and LR chi2(10) = 1530.58. Log likelihood = −3798.2325 (Prob > chi2 = 0.0000, Pseudo *R*2 = 0.1677).

Through the analysis of **Tables 8** and **9**, we can conclude that delivery men are more likely to run red lights and ride retrogradely, this shows a different result than the logit model in **Table 7**. This may have something to do with the mandatory wearing of safety helmets for delivery men.

6. Discussion

Due to their fast speed, convenient use, and low price, more and more people have chosen to ride e-bikes in recent years. The number of e-bikes has reached a considerable number and still maintains a high growth rate. There is an apparent contradiction between the rapid popularization of e-bikes and the backward management system, and there is more and more traffic chaos involving e-bikes.

From the epidemiological study of road traffic accidents related to e-bikes, with the popularization of e-bikes, traffic accidents related to e-bikes are increasing daily. In these accidents, e-bike riders are often seriously injured because of a lack of protection and the characteristics of fast speed and poor stability of e-bikes. In accidents of collision with motor vehicles, the proportion of severe injuries and even deaths of electric two-wheeler riders are higher than drivers and passengers of motor vehicles. In road use, electric two-wheeler riders belong to a vulnerable group and are a fragile means of transportation.

However, the results of this study show that electric two-wheeler riders who use fragile means of transportation show very aggressive riding behavior when riding e-bikes. Nearly 40% of the incidents of illegal behaviors indicate that electric two-wheeler riders pay little attention to traffic rules when riding e-bikes. At the same time, Through the analysis of the subjective dangerous behaviors of electric two-wheeler riders, we can conclude that whether there is a traffic controller greatly impacts whether electric bike riders will engage in active dangerous behaviors. This study postulates that fear of punishment is a critical factor in restraining e-bike riders, similar to the previous research results. This study observed the dangerous driving behavior of electric two-wheeler riders on sunny and rainy days and found that the frequency of active hazardous driving behavior of electric two-wheeler riders on sunny days was significantly higher than on rainy days, which is inconsistent with our view that e-bike riders are more likely to take illegal actions to increase their driving comfort in bad weather conditions.

The research suggests that this may be caused by the mentality of electric two-wheeler riders who are more worried about being hurt on rainy days; After analyzing and discussing the gender of electric two-wheelers who take dangerous riding behaviors, it is found that male riders are higher than female riders in terms of both the frequency of passive and active hazardous behaviors, which is consistent with Yang (2015). Men are more likely to take risky behaviors than women. Among cyclists who have observed dangerous riding behaviors, the logistic regression analysis shows that age difference does not significantly impact whether cyclists have active hazardous behaviors.

Electric cyclists who don't wear safety helmets account for a high proportion of 6449 cyclists who have observed dangerous behaviors. How to regulate EB wearing helmets when riding e-bikes should be the focus of urban traffic law enforcement departments.

According to the epidemiological study of road traffic injuries and the data obtained based on natural observation in this study, we can generally conclude that e-bikes are a very fragile means of transportation but have very aggressive users. Based on the chaotic scene of complex urban traffic and e-bikes running rampant, urban traffic law enforcement departments should strengthen safety education for e-bike drivers, establish more perfect traffic regulations for e-bikes, and strictly regulate the riding behavior of e-bikes. At the same time, traffic law enforcement departments should increase the punishment for illegal e-bike riders, make clear the subject of responsibility in the face of accidents of e-bikes and motor vehicles, and not blindly take care of the "weak" side in the road environment.

The results of this study provide the following policy recommendations. First of all, our research results show that the presence or absence of traffic controllers impacts the risk-taking behavior of non-motorized vehicle riders, which plays a vital role in the traffic management department's reasonable arrangement of the distribution of traffic controllers. On average, the incidence of risk-taking behavior of non-motorized vehicle riders in sections with traffic controllers is 0.821 times that in sections without traffic controllers. Secondly, EB and EM are two types of non-motorized vehicles that account for a very high proportion in China. Their riders tend to take more adventurous riding behaviors than bicycle riders. At present, China has a large number of EB and EM. It is necessary to set special laws and regulations on EB and EM. The New National Standard for e-bikes positively affects road safety through the speed limit enforcement of e-bikes, and all parts of China have also managed e-bike license plates and achieved remarkable results. Even though e-bikes are already subject to speed limits, residents' perceptions of the convenience and speed of e-bikes are still difficult to change. Traffic police are still under pressure to investigate and penalize e-bikes who break the maximum design speed limit. Consideration needs to be given to ensuring that management is in effect. Thirdly, after analyzing observation data, we found that not wearing a safety helmet is the highest proportion of all non-motorized vehicle riders' risky behavior. Olivier's (2021) research shows that helmet use was associated with a 50% lower risk of head injury and a 21% lower risk of facial injury. How to restrict non-motorized vehicle riders to wear safety helmets correctly as required is a problem that traffic management departments need to consider. Fourth, we note that non-motorized cyclists at intersections with special non-motorized lanes are more likely to take risky actions. In addressing conflicts at signalized intersections, Bai et al. (2013) conducted a comparative analysis highlighting the safety implications of e-bikes. Their findings indicate that e-bikes increase the complexity of traffic dynamics at intersections, leading to higher conflict rates than traditional bicycles (Bai, 2013). This aligns with our observation of increased accident rates at these locations, underscoring the need for tailored traffic management strategies for e-bikes.

Coordinating the relationship between motor vehicles and non-motorized vehicles in the sections with special non-motorized lanes and mitigating the conflict between motor vehicles and non-motorized vehicles is also a problem that needs to be considered by traffic management departments in policy formulation. Fifth, delivery men will not significantly increase the incidence of risky behavior. This is due to the mandatory wearing of safety helmets for delivery men. Other aggressive riding behaviors of delivery men were still obvious. This is consistent with the findings of Zhang et al. (2023). Previous research shows that delivery men usually suffer more serious injuries due to faster speed, and the delivery staff usually ride heavier and longer endurance heavy e-bikes. Strengthening the management of the delivery men is still vital work. Sixth, the study found that e-bike riders in the suburbs are more likely to take risky riding behaviors, combined with the characteristics of poor road conditions, imperfect lighting facilities, and unpopular monitoring, e-bike riders in the suburbs are more likely to be injured by traffic accidents and difficult to be found and dealt with in time after traffic accident injuries, which may cause more serious consequences.

Our analysis of urban versus suburban accident rates finds distinction in the study by Zhang et al. (2023), who examined factors influencing the market share of e-bike sharing in New York City. They noted that urban areas, due to their higher traffic density and complexity, exhibit a higher incidence of e-bike accidents. More surveillance cameras, traffic controllers, and warning signs on suburban roads may help reduce risk-taking among e-bike riders. Our research complements past neglect of e-bike safety in the suburbs. Finally, previous studies have noted that peak periods have the highest probability of road accidents worldwide (Zhu et al., 2021). The study found that e-bike riders are more inclined to take risky riding behaviors during flat peak hours, which may be related to the larger traffic flow during peak hours, which makes riders dare not take risky behaviors. It may also be related to the reason that there are fewer traffic controllers during off-peak hours. All in all, paying attention to the management of electric bike riders during peak hours will effectively reduce the incidence of risk-taking behavior of electric bike riders.

Notably, all three models indicate that the incidence of risky behaviors among non-motorized vehicle riders in urban areas is higher than in suburban areas. This suggests that the management of non-motorized vehicle riders in cities needs to be further strengthened.

7. Conclusions

This research not only highlights the prevalence of risk-taking behaviors among e-bike riders and their significant impact on traffic accident rates but also proposes a series of data-driven safety interventions. By implementing these measures, we can expect a notable reduction in e-bike-related accidents and injuries, enhancing the overall safety of all road users. Moreover, the findings of this study are crucial for policy-making targeted at the rapidly growing e-bike user demographic, contributing to the promotion of a safer, more sustainable urban transportation system. Based on this study, the following conclusions were drawn:

1) With the increase in the number of e-bikes, the number of traffic accidents involving e-bike riders is also increasing. Compared with traditional motor vehicle drivers, e-bike riders often suffer more serious injuries due to their lack of more effective protection measures. Similarly, higher speeds can cause more serious injuries than traditional bike riders due to the electrically driven nature of e-bikes.
2) The results of natural observation showed that e-bike riders have a higher incidence of risk-taking behavior. Even compared to cyclists, EB had a higher incidence of every risky behavior. This is different from our view that the less safe a vehicle user should be, the more cautious they should be. The reason for this phenomenon may be closely related to the overly flexible nature of the e-bike itself and the difficult characteristics of its forward trajectory.
3) The results of the binomial logit model show the factors that affect whether e-bike riders will take risky behaviors. Our analysis found that the factors commonly associated with impulsivity, risk-taking, and fluke make e-bike riders more likely to take risks.
4) Based on the binomial logit model results, this study offers policy recommendations to regulate e-bike riders' behavior and enhance their safety. The recommendations included stricter enforcement of traffic laws and mandatory safety training for e-bike riders, which are essential to mitigate the risks associated with e-bike use.
5) In addition, this study only observed the dangerous behavior of non-motorized vehicle riders, and did not link the dangerous behavior of non-motorized vehicle riders with the serious consequences of traffic accidents after non-motorized vehicle riders took dangerous behaviors, nor did it take into account the psychological activities of non-motorized vehicle riders in taking dangerous behaviors, so further investigation should be continued in the future.

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