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Analysis of factors affecting injury severity of shared electric bike riders

Zhang Xiaolong[1] Huang Jianling[1,2] Bian Yang[1] Zhao Xiaohua[1] Li Jia[1]

([1]Faculty of Architecture, Civil and Transportation Engineering, Beijing University of Technology, Beijing 100124, China)
([2]Beijing Intelligent Transportation Development Center, Beijing 100073, China)

Abstract: This study investigated the potential factors affecting the injury severity of shared electric bike (e-bike) riders and analyzed potential heterogeneity using a dataset comprising of 1 343 shared e-bike insurance accidents recorded by a shared e-bike company as the research object. The injury severity was categorized into two levels: not injured and injured. Twelve independent variables were selected based on six aspects involving attributes of shared e-bike rider, vehicle, road, environment, time, and accident. The effects of different factors on the injury severity of shared e-bike riders were assessed using the random parameter logit model with heterogeneity in means. Results indicate that the variable "other traffic participants at fault" in the accident scenarios featured a random parameter that adhered to a normal distribution and exhibited mean heterogeneity. This increased the likelihood of injury among shared e-bike riders. However, the probability of injury decreased when the scenario involved both the variable "other traffic participants at fault" and component damage. The variables female, intact road surface, dry road pavement, nighttime, single-vehicle accidents, and both at-fault accidents could increase the injury probability among shared electric bike riders to varying degrees. The findings of this research provide a theoretical basis for the development of traffic safety strategies targeted at shared electric bike riders.

Key words: traffic engineering; injury severity; shared electric bike riders; random parameter model; heterogeneity in mean

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Under China's rapid economic development, rapid industrialization progress, and continuous urbanization, cities continue to expand. Consequently, road network traffic has increased, and traffic travel distances continue to rise. Owing to their speed, convenience, and cost-effectiveness, electric bikes (e-bikes) have become an essential means of urban transportation for short distances[1]. In recent years, China's e-bike market has experienced rapid growth, with the social ownership of e-bikes reaching nearly 300 million[2]. However, the issue of e-bike traffic safety has become more pronounced. In 2019, e-bike-related casualties accounted for about 70% of the nonmotor vehicle losses in national road traffic accidents[3].

In recent years, the rapid advancement of Internet technology has led to an emerging service industry represented by shared e-bikes. By 2019, the number of shared e-bikes had exceeded 1×10^6[4]. Moreover, shared e-bikes have introduced certain safety concerns owing to poor management and insufficient fundamental investment. In addition, the simple registration procedure of the platform[5] and the inappropriate age limit for riders[6] have resulted in a low entry barrier for shared e-bikes, thereby posing a significant safety risk. Moreover, some riders lack proper driving skills and legal awareness[7], contributing to repeated traffic violations such as wrong-way riding, thereby increasing the risk of traffic accidents. Research indicates a rising trend in traffic accident injuries involving shared e-bikes[8]. Therefore, investigating the traffic safety challenges posed by shared e-bikes to propose reasonable improvement suggestions will help alleviate the pressure on traffic safety management and assist in safety prevention and control.

In recent years, numerous scholars have performed extensive research on the safety risks and accidents associated with private e-bikes. Hertach et al.[8] obtained e-bike accident data through questionnaires and used a binomial logit model to analyze the influence of various factors such as individual, vehicle, road, and environmental attributes on the accident injuries of e-bike riders. Their findings revealed that accident injuries are more prevalent among women, older adults, riders traveling at speeds up to 45 km/h, and those who perceive their physical condition as inferior to those of their peers. Panwinkler et al.[9] extracted e-bike accident data based on accident text and used an ordered probability model for research. They found that excessive speed, drinking alcohol, and downhill riding can cause serious injury to e-bike riders. Dong et al.[10] analyzed the factors affecting accident injury based on accident video data involving e-bike collisions with cars using binomial logit and multiple logit models

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Biographies: Zhang Xiaolong (1996—), male, Ph. D. candidate; Bian Yang (corresponding author), female, doctor, professor, bianyang@bjut.edu.cn.

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and compared the prediction accuracies of the two models.

The aforementioned research indicates that scholars have achieved specific advancements in the investigation of personal e-bike traffic accident injuries. However, the research on shared e-bike traffic accident injuries remains inadequate. Given the numerous differences between shared and private e-bike riders across various facets, including mental and physical health and riding behavior characteristics[6-7], it remains uncertain whether the outcomes of accident causation analysis and the corresponding improvement measures derived from the private e-bike riding group can be applied to the shared e-bike riding group. Consequently, for the emerging demographic of shared e-bike riders, reanalyzing the mechanism behind the impact of traffic accidents and formulating targeted measures to enhance traffic safety are imperative. Moreover, although numerous studies have modeled e-bike traffic accident injuries and analyzed causal relations, several unresolved or overlooked issues persist, such as the heterogeneity of e-bike accident injury data. The discrete choice model utilized in the aforementioned research, particularly the conventional logit regression model, cannot effectively identify unobserved heterogeneity in the traffic accident data[11]. Heterogeneity arises when specific variables influencing accident severity are omitted from the model or when correlations exist between variables in the model and omitted variables. Studies have demonstrated that variables such as the physiological characteristics of drivers[12], traffic violations[13], and road lighting[14] are affected by other variables in the model during traffic accident analysis. This results in biased model outcomes and an inability to accurately analyze potential interaction relations among factors affecting e-bike traffic accident injuries.

Several scholars have utilized the random parameter logit (RP-logit) model to address heterogeneity in traffic accident data. Chen et al.[15] employed the RP-logit model to assess injury severity in single-car and multicar accidents involving trucks on rural roads. Kim et al.[16] investigated the effect of driver age and gender on injury severity in single-vehicle collision accidents using the RP-logit model. The RP-logit model allows explanatory variables to be spontaneous; however, individual heterogeneity in the random parameters can still exist. To address this issue, Mannering et al.[17] introduced a method that relates the mean and variance of random parameters with other explanatory variables in the model when analyzing highway traffic accidents to determine individual heterogeneity. Yang et al.[18] employed the RP-logit model with heterogeneity in means and variances (RP-logit-HMV) to explore the heterogeneity of factors affecting the severity of accidents involving nonhelmeted motorcycle riders and various vehicle types. The abovementioned study thoroughly investigates the effect of heterogeneity on the modeling and analysis of motor vehicle traffic accidents, introducing novel perspectives to traffic accident analysis. Therefore, incorporating the RP-logit or RP-logit-HMV models proves advantageous in addressing heterogeneity in shared e-bike injury data and investigating potential interactions among variables.

In this research, data on shared e-bike insurance accidents from a shared e-bike enterprise during the period of May to September 2020 were obtained. Combining information such as shared e-bike riders', accident, road, and weather attributes, the RP-logit-HMV, RP-logit, and binomial logit models were used for fitting and comparative analysis. Furthermore, the optimal model was used to analyze the injury severity of shared e-bike riders and provide a theoretical basis for developing traffic safety strategies to protect shared e-bike riders.

1 Data Preparation

The dataset used in this research was comprised of two components. 1) 2 667 shared e-bike accident data spanning from May to September 2020, sourced from an insurance accident management platform of a shared e-bike company. The platform documents accident specifics, including location, time, causation, and detailed information about the accident, along with the name, gender, and date of birth of the rider for each insured accident. After deleting the missing values in the original data, 1 343 accidents were retained as the foundational dataset for this research. 2) Historical weather data, including weather conditions, temperature, wind direction, and other relevant indicators, were retrieved from a query website[19]. We aligned the weather data with the time and location of each accident to establish an accurate correlation.

The traffic accidents in the insurance accident database of the shared e-bike company are divided into three categories—not injured, injured, and fatal accidents—based on the injury severity of shared e-bike riders. Among the 1 343 accidents obtained, 395 were not injured accidents, 945 were injured accidents, and three were fatal accidents. Considering that fatal accidents account for only a small proportion of the sample, they were combined with injured into one level, namely injured, for subsequent modeling analysis.

The transportation system encompasses a multitude of factors, including traffic participants, vehicles, roads, and the environment. Any problem within these elements could potentially result in traffic safety issues and cause accidents. Therefore, considering the effect of various factors on accidents, 12 variables were selected based on shared e-bike rider, vehicle, road, and environmental attributes as candidate explanatory variables. The coding and descriptive statistics for each explanatory variable are presented in Tab. 1.

Tab. 1 Descriptive statistics for variables

Variable type	Variable	Description	Code	Number	Percentage/%
Shared e-bike riders' attributes	Gender	Male#	0	703	52.345
		Female	1	640	47.655
	Age	<18 (adolescent)#	0	32	2.383
		18 to 45 (youth)	1	1 216	90.544
		46 to 59 (middle-aged person)	2	95	7.074
Vehicle attributes	Vehicle status	Normal#	0	1 078	80.268
		Component damage (vehicles have faults such as brake or steering failure)	1	265	19.732
Road attributes	Site	Road section#	0	1 189	88.533
		Intersection	1	154	11.467
	Road surface	Intact#	0	1 224	91.139
		Damaged (uneven road surface or the presence of pits, ditches)	1	119	8.861
	Road pavement	Dry#	0	1 279	95.235
		Wet (wet and waterlogged roads)	1	64	4.765
Environmental attributes	Weather	Sunny#	0	941	70.067
		Adverse weather (rainy and foggy weather)	1	402	29.933
	Lighting	Daytime#	0	826	61.504
		Nighttime	1	517	38.496
Time attributes	Time interval	Nonpeak period#	0	951	70.812
		Peak period (7:00—9:00, 17:00—19:00)	1	392	29.188
	Day of the week	Weekday#	0	980	72.971
		Weekend	1	363	27.029
Accident attributes	Fault	Riders at fault# (when the rider bears full or primary responsibility for the collision)	0	937	69.769
		Both at fault (when both the rider and the other traffic participant share equal responsibility for the collision)	1	108	8.042
		Other traffic participants at fault (when the other traffic participant is fully or primarily responsible for the collision)	2	298	22.189
	Form	Single-vehicle accident# (including riders falling, being thrown, and hitting fixtures)	0	785	58.451
		Vehicle-pedestrian accident (accidents caused by collisions between e-bikes and pedestrians)	1	116	8.637
		Vehicle-to-vehicle accident (accidents caused by collisions between e-bikes and other vehicles)	2	442	32.911

Note: # represents the model reference category.

2 Method

2.1 Random parameter logit model with heterogeneity in means and variances

The utility function for the injury severity of shared e-bike riders is shown as follows:

$$S_{in} = \boldsymbol{\beta}_i \boldsymbol{X}_{in} + \varepsilon_{in} \tag{1}$$

where S_{in} represents a severity function determining the probability of injury severity category i (not injured, injured) in crash n; $\boldsymbol{X}_{in}$ represents the vector of explanatory variables; $\boldsymbol{\beta}_i$ represents a vector of estimable parameters; ε_{in} represents the random error.

Allowing heterogeneity in the means and variances of random parameters entails reformulating Eq. (1) so that $\boldsymbol{\beta}_{in}$ becomes a vector of estimable parameters that varies across observations.

$$\boldsymbol{\beta}_{in} = \boldsymbol{\beta}_i + \boldsymbol{\delta}_{in}\boldsymbol{Z}_{in} + \sigma_{in}\exp(\boldsymbol{\omega}_{in}\boldsymbol{W}_{in})\, v_{in} \tag{2}$$

where $\boldsymbol{\beta}_i$ represents a mean parameter estimate in all accidents; $\boldsymbol{Z}_{in}$ represents a vector of attributes that represents heterogeneity in the means; $\boldsymbol{\delta}_{in}$ represents a corresponding vector of estimable parameters; $\boldsymbol{W}_{in}$ represents a vector of attributes that captures heterogeneity in the standard deviation σ_{in} with parameter vector $\boldsymbol{\omega}_{in}$; v_{in} represents a disturbance term (a term with a random distribution that captures unobserved heterogeneity among accidents).

The probability of injury severity category i attributable to the crash n, $P_n(i)$, is expressed by allowing the vector $\boldsymbol{\beta}_{in}$ to obtain a continuous density function, implying that $\text{Prob}(\boldsymbol{\beta}_n = \boldsymbol{\beta}) = f(\boldsymbol{\beta} \mid \boldsymbol{\varphi})$,

$$P_n(i) = \int \frac{\exp(\boldsymbol{\beta}_i \boldsymbol{X}_{in})}{\sum\limits_{\forall I} \exp(\boldsymbol{\beta}_i \boldsymbol{X}_{in})} f(\boldsymbol{\beta} \mid \boldsymbol{\varphi})\, \mathrm{d}\boldsymbol{\beta} \tag{3}$$

where $f(\boldsymbol{\beta} \mid \boldsymbol{\varphi})$ represents the density function of $\boldsymbol{\beta}$ with $\boldsymbol{\varphi}$

referring to the vector of parameters (mean and variance) of that density function, and other terms are as previously defined.

2.2 Marginal effect

The RP-logit-HMV cannot quantify the magnitude of the effect of each explanatory variable on the probability of the injury severity outcome; therefore, the marginal effect is used to evaluate the effect of a unit increase in each explanatory variable on the probability of the injury severity outcome. The marginal formula is shown as follows:

$$E_{x_{kin}}^{P_{in}} = \frac{P_{in}(x_{kin}=1) - P_{in}(x_{kin}=0)}{P_{in}(x_{kin}=0)} \tag{4}$$

where x_{kin} represents the value of explanatory variable k for accident n in the injury severity category i and $P_{in}(x_{kin}=0)$ and $P_{in}(x_{kin}=1)$ represent the probability of the injury severity category i for accident n when x_{kin} equals 0 and 1, respectively; $E_{x_{kin}}^{P_{in}}$ can be interpreted as the change in the probability of the injury severity category i when a discrete variable x_{kin} changes from 0 to 1.

2.3 Binomial logit model

A binomial logit model is used as a comparison model herein. The logit regression equation can be expressed as follows:

$$\log\left(\frac{P}{1-P}\right) = \beta_0 + \boldsymbol{\beta X} \tag{5}$$

where P represents the probability when the injury severity is classified as injured; $\boldsymbol{X}$ represents the vector of explanatory variables, $\boldsymbol{\beta}$ represents a vector of estimable parameters; β_0 represents a constant.

When injured, the injury severity probability for a given value of the vector of explanatory variables $\boldsymbol{X}$ can be theoretically calculated as follows:

$$P = \frac{\exp(\beta_0 + \boldsymbol{\beta X})}{1 + \exp(\beta_0 + \boldsymbol{\beta X})} \tag{6}$$

3 Parameter Identification and Results

3.1 Parameter identification

In this study, the NLogit software and the Monte Carlo method were used to establish the RP-logit model with heterogeneity in means and variances, with a significance level of 0.1. The solution process was as follows:

1) As no closed-form solution exists for the coefficient solution of the RP-logit-HMV, only the simulation solution can be used. The simulation solution involves random and Halton sequence sampling. The Halton sequence sampling exhibits high efficiency and uniform distribution of sampling points. Consequently, the paper adopted Halton sequence sampling, with a sampling frequency of 200[11].

2) Before model estimation, the specification of the probability density function for the parameters was essential. Probability density function forms of parameters exhibit uniform distribution, normal distribution, and log-normal distribution. The normal distribution is superior to other probability density functions[20]. Therefore, it was assumed that all explanatory variables to be estimated were random parameters, and the parameters to be evaluated were assumed to follow a normal distribution in the simulation. The simulation results revealed that the opposing side of the accident fault exhibited the attributes of random parameters, and the remaining explanatory variables were fixed parameters.

3) The RP-logit-HMV was established along with the RP-logit and binomial logit models using the NLogit software. The parameter estimation results are shown in Tab. 2. Notably, no variance heterogeneity existed in the model; thus, RP-logit-HMV eventually degenerates into the RP-logit model with heterogeneity in means (RP-logit-

Tab. 2 Parameter estimation of the three logit models

Variables		Binomial logit		RP-logit		RP-logit-HM	
		Coefficient	Sig.	Coefficient	Sig.	Coefficient	Sig.
Constant		1.741	0.000	1.804	0.000	1.760	0.000
Fixed parameter	Female	0.305	0.027	0.341	0.030	0.338	0.027
	Component damage	−0.626	0.001	−0.381	0.107	−0.159	0.501
	Damaged road surface	−0.641	0.011	−0.595	0.039	−0.687	0.013
	Wet road pavement	−0.833	0.008	−0.871	0.014	−0.913	0.007
	Nighttime	0.294	0.040	0.272	0.096	0.294	0.064
	Both at fault	0.524	0.028	0.705	0.004	0.699	0.005
	Other traffic participants at fault	0.707	0.000				
	Vehicle-pedestrian accident	−3.452	0.000	−3.595	0.000	−3.579	0.000
	Vehicle-to-vehicle accident	−1.924	0.000	−2.223	0.000	−2.185	0.000
Random parameter	Other traffic participants at fault			2.456	0.042	2.028	0.005
Heterogeneity in the mean of the random parameter	Other traffic participants at fault: Component damage					−1.964	0.001

HM). The comparison of the three models is presented in Tab. 3. The log-likelihood value of the RP-logit-HM was −658.161, with an Akaike information criterion (AIC) value of 1 340.300, a Bayesian information criterion (BIC) value of 1 402.800, an R^2 value of 0.293, and an adjusted R^2 value of 0.287. The results reveal that the RP-logit-HM exhibits a better fit and interpretation.

3.2 Results

Comparing the results of the RP-logit-HM with the RP-logit and binomial logit models revealed that the influence of factors such as female, damaged road surface, wet road pavement, nighttime, both at fault, vehicle-pedestrian accident, and vehicle-to-vehicle accident on the injury severity of shared e-bike riders were in the same direction (see Tab. 2). In contrast, in the case of other scenarios such as those involving different traffic participants at fault and component damage, the RP-logit-HM identified the stochastic and heterogeneous attributes of these variables, thereby mitigating potential biases in model parameter estimation and inference. Consequently, only the parameter outcomes of the RP-logit-HM model are discussed in subsequent sections of the paper.

3.2.1 Random parameter

According to Tab. 2, the variable "other traffic participants at fault" within accident scenarios followed a normal distribution of random parameters. As shown in Fig. 1, the variable "other traffic participants at fault" followed a normal distribution characterized by a mean of 2.028 and a standard deviation of 2.175. This indicates that about 82.380% of shared e-bike riders in accidents were more susceptible to injuries when other traffic participants were at fault. In contrast, about 17.620% of shared e-bike riders were less prone to injury if the accident was attributed to other traffic participants.

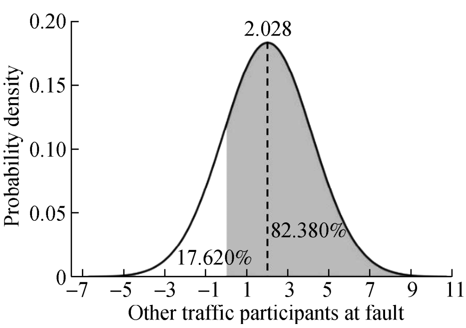

Fig. 1 Distribution of random parameters

3.2.2 Heterogeneity in the mean of the random parameter

Tab. 2 shows that the mean of the random parameter for the variable "other traffic participants at fault" was influenced by vehicle status, specifically component damage. The mean value of the random parameter for the variable "other traffic participants at fault" exhibited a negative correlation with the presence of component damage in the vehicle. As shown in Fig. 2, the mean value of the parameter for accidents involving other traffic participants at fault was 2.028 and decreased to 0.064 when the accident involved component damage. The result suggests that while the likelihood of injury among shared e-bike riders increased when other traffic participants were at fault, the presence of component damage mitigated this escalation. One possible explanation is that the shared e-bike platform promptly immobilized and prohibited the use of vehicles after a user reported vehicle component damage. Consequently, this measure curtailed accidents arising from vehicle component damage, thereby reducing the likelihood of rider injury.

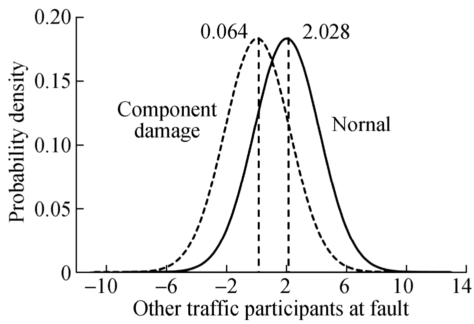

Fig. 2 Distribution of random parameters with heterogeneity in means for other traffic participants at fault

3.2.3 Fixed parameter

According to the model calculation results (see Tab. 3), several factors exhibited significant effects on the injury severity of shared e-bike riders. Hence, in this section, the factors influencing injuries sustained by shared e-bike riders, in conjunction with marginal effects (see Tab. 4), were analyzed.

1) Shared e-bike riders' attributes. The gender of

Tab. 3 Measure-of-fit of the three logit models

Statistic	Binomial logit	RP-logit	RP-logit-HM
Log-likelihood value	−669.208	−664.146	−658.161
AIC	1 358.400	1 350.300	1 340.300
BIC	1 410.400	1 407.500	1 402.800
R^2	0.178	0.287	0.293
Adjusted R^2	0.171	0.281	0.287

Tab. 4 Marginal effect of various parameters in the RP-logit-HM

Variables	Marginal effects
Female	0.022
Component damage	−0.004
Damaged road surface	−0.009
Wet road pavement	−0.007
Both at fault	0.015
Nighttime	0.012
Vehicle-pedestrian accident	−0.045
Vehicle-to-vehicle accident	−0.142

shared e-bike riders significantly influenced injury severity. Following accidents, female shared-e-bike riders displayed a higher likelihood of injury than males, with the probability of female injury escalating by 2.200%. This trend is attributable to multiple factors, such as the greater weight of shared e-bikes, the potential difficulties female riders face in maneuvering these bikes, and the less ability of female riders to control and react to accidents compared with males[21]. The above factors led to a higher probability of injury for female shared e-bike riders than males after an accident.

2) Road attributes. The condition of the road surface significantly influenced the severity of accident injuries. The likelihood of shared e-bike riders sustaining injury under damaged road surface conditions was 0.900% lower than that under intact road surface conditions. Moreover, the state of the road pavement significantly affected injury severity, and the likelihood of shared e-bike riders sustaining injuries under wet road pavement conditions was 0.700% lower than that under dry pavement conditions. Interestingly, previous research yielded inconsistent results concerning the effects of road surface and pavement on accidents. Wang[1] found that road pavement did not significantly influence accident severity. In contrast, Hertach et al.[8] identified damaged roads and difficulties maintaining balance owing to wet road surfaces as significant accident contributors. Although riding under conditions of damaged road surfaces and wet road pavement entails elevated risk, our research indicated that accidents might not necessarily occur, attributable to a shift in the psychological approach of shared e-bike riders when confronted with unfavorable road conditions. Riders often adopt anticipatory measures, exhibiting defensive driving behaviors such as heightened focus and cautious operation to mitigate the risks associated with poor road conditions.

3) Environmental attributes. The likelihood of causing injury to shared e-bike riders was higher during nighttime than during the daytime, with the probability of injury for those traveling at night increasing by 1.500%. This phenomenon is attributable to reduced rider visibility and the accelerated speeds of shared e-bikes during nighttime. These factors lead to diminished perception and reaction time for accident participants to evade danger or mitigate personal harm[22].

4) Accident attributes. Both accident fault and accident form displayed significant effects on injury severity. Relative to single-vehicle accidents, incidents involving vehicle-pedestrian and vehicle-to-vehicle collisions were 4.500% and 14.200% less likely to cause injury to shared e-bike riders, signifying that single-vehicle accidents were more prone to causing injuries. This outcome diverged from findings in prior research[23]. Riders might be unfamiliar with the structural mechanics of shared e-bikes, potentially leading to improper or excessively abrupt braking and unsuitable or excessive speeds[8]. Inexperienced riding and a lack of awareness regarding traffic safety among shared e-bike riders could also contribute to these disparities[24]. Traffic management must prioritize the safety of shared e-bike riders. When both parties are at fault in an accident, the likelihood of injury for shared e-bike riders increases by 1.200% compared with accidents where only the rider is responsible. This is attributable to the reduced reaction time for shared e-bike riders in situations involving mutual fault, thereby elevating the risk of injury[1].

The results of the paper could provide a basis for improving the traffic safety of shared e-bike riders: 1) The mean heterogeneity of “other traffic participants at fault” and component damage reveals that while component damage can mitigate the degree of injury escalation, regular vehicle inspections and maintenance by shared e-bike enterprises are essential to enhance vehicle safety performance. 2) To address road surface, pavement, and lighting factors, governmental initiatives should focus on enhancing road traffic facilities, optimizing riding environments, incorporating road lighting facilities, and reinforcing road maintenance efforts. 3) Addressing gender discrepancies, accident faults, and accident forms necessitates increased traffic safety advocacy by traffic management authorities. Moreover, the awareness of law-abiding behavior should be enhanced, with specific attention to training programs for women and other vulnerable groups to enhance their protection awareness.

4 Conclusions

1) The variable “other traffic participants at fault” exhibited characteristics of a random parameter with a normal distribution and demonstrated mean value heterogeneity within accident fault scenarios. Specifically, when the vehicle had component damage, accidents in which the fault lay with other traffic participants resulted in an increased likelihood of injury to shared e-bike riders. However, the presence of component damage could mitigate the extent of this increase.

2) The model estimation and marginal effect outcomes highlight that various factors—such as female riders, intact road surfaces, dry road pavements, nighttime incidents, single-vehicle accidents, and accidents involving both parties at fault—contribute to varying degrees in elevating the probability of injury among shared electric bike riders.

3) This study elucidated the factors influencing injury severity among shared e-bike riders. According to insurance accident data, potential data heterogeneity was addressed. The insights provided serve as valuable references for shaping policies aimed at enhancing the safety of shared e-bike traffic systems. Nevertheless, certain limitations exist within this study. The insurance accident

records for shared e-bikes cannot cover all pertinent accident-related information. Future research could more comprehensively analyze factors impacting the injury severity of shared e-bike riders by obtaining more accurate and comprehensive shared e-bike traffic accident data. Moreover, according to the extensive data from shared e-bike trajectories, an all-encompassing analysis of safety, incorporating risky riding behaviors, and proposing corresponding enhancement measures could better elucidate the current state of shared e-bike safety.

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共享电动自行车骑行者事故伤害严重程度影响因素分析

张晓龙[1]　黄建玲[1,2]　边　扬[1]　赵晓华[1]　李　佳[1]

([1] 北京工业大学城市建设学部, 北京 100124)
([2] 北京市智慧交通发展中心, 北京 100073)

摘要:以某共享电动自行车企业的 1 343 起出保险事故为研究对象,分析影响共享电动自行车骑行者事故伤害严重程度的潜在因素及可能存在的异质性. 将伤害严重程度分为未受伤和受伤 2 个等级,从共享电动自行车骑行者属性、车辆属性、道路属性和环境属性等因素中选取 12 个自变量进行分析. 通过构建均值异质性随机参数 Logit 模型,探究了不同因素对共享电动自行车骑行者伤害严重程度的影响. 结果表明:事故责任中的变量"其他交通参与者责任"具有服从正态分布的随机参数特征,且具有均值异质性,表现为事故责任是其他交通参与者的事故会增加共享电动自行车骑行者受伤的可能性,机件故障则能减少其增加幅度;女性、路面平整度良好、路表状态干燥、夜间、单车事故、双方责任事故会不同程度地增加共享电动自行车骑行者受伤的概率. 研究结果为制定保障共享电动自行车驾驶者交通安全的策略提供理论依据.

关键词:交通工程;事故伤害严重程度;共享电动自行车骑行者;随机参数模型;均值异质性
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