TO GET A BETTER UNDERSTANDING OF E-BIKE SAFETY IN CHINA, A GENERALISED ORDERED LOGIT MODEL WAS USED TO PREDICT THE SEVERITY OF CRASHES

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ABSTRACT:
A comprehensive crash modelling effort was performed in order to investigate the severity of injuries sustained by e-bicyclists. This model, known as a generalised ordered logit model, was used because it is able to capture the ordinal character of injury severity while still allowing for variability among data. There are a number of indicators that have been discovered that are connected with the severity of injuries sustained by e-cyclists. These factors include the e-cyclist being older, there being a big vehicle involved, the e-cyclist being at fault, the e-cyclist turning left, the e-cyclist crossing the road, the driver turning right, being in an industrial area, during the weekday, and having tree separation. The results of the modelling are used to propose safety countermeasures and interventions, such as developing educational programmes for specific age groups (such as older e-bicyclists, female e-bicyclists, and inexperienced drivers), launching safety campaigns, improving geometric design and traffic control in low-developed areas, curve roads, and signalised intersections, and so on. Furthermore, some interesting research topics have been suggested, such as investigating the mechanism of a crash involving a head-on e-bike collision, the mechanism of a collision involving e-bicyclists, heavy trucks, and motorcycles, and the safety effects of various separation treatments on the severity of injuries sustained by e-cyclists from both a kinetic and a kinematic point of view.
E-bike, injury severity, a generalised ordered logit model, and crash mechanism are some of the keywords that should be considered.

I.INTRODUCTION:
In recent years, e-bicycles have gradually become the most priority commuting tool for urban citizens in China. e-bicycles can travel faster than regular bikes and have lower energy-cost than automobiles. Till the end of year 2014, the ownership of e-bicycles in China has been reaching 2.0 billion, with the increasing speed of 20% per year.1 In China, e-bicycles are categorized into nonautomobiles and are allowed to share roads with bikes. However, there are no mandatory regulations on license, insurance and helmets for e-bicycles. With the rapid increase in the e-bicycle ownership, e-bicycle related crashes have been significantly increasing. In 2008,2 about 5107 e-bicycle riders died in traffic crashes, accounting for 5.4% of total fatal crashes. In 2014, this figure has reached 7.8%.3 Due to a large increase in the injuries and deaths in e-bicycle crashes, improving road safety for e-bicyclist is important for transport engineers.4 Various modeling approaches have been applied to examine the injury severity of bicyclist, although limited research has focused on e-bicycle crashes for improving road safety for the e-bicyclist.5 This research attempts to fill the gap, by investigating characteristics of factors, which include driver characteristics (age, gender, driver years, etc.), roadway characteristics (road type, number of traffic lanes, bicycle-motor separation type, etc.), environmental factors (time, weather, visibility, etc.), location, party at fault, crash types, e-bicyclist and driver behavior, and the land use characteristics specifically. This article uses data drawn from the traffic crash treatment center of Guilin Police Department in southern China for crash modeling.

II.Literature review

Weinert et al.6 examined safety perceptions of ebicyclists by surveying e-bicycle riders in Shijiazhuang City in China. Their findings include (1) e-bicyclists feel satisfied and safe when traveling; (2) female riders feel safer riding e-bicycles to cross intersections than bicycles. Feng et al.7 examined the trend of e-bicyclerelated injuries in China. It was found that e-bicyclerelated injuries and deaths were experiencing a significant increase in recent years while overall traffic and bike-related injuries and deaths were decreasing. It was pointed out that e-bicycle safety had become a serious problem that deserves more attention in China. Yao and Wu8 conducted a self-reported questionnaire survey on e-bicyclists in two large cities in China. From the responses of e-bicyclists, it was found that gender and automobile driving experiences were highly correlated with at-fault e-bicycle-related crashes. Males were found to be more likely to be involved in at-fault crashes than females. e-bicyclists with driving licenses were found to be less likely to be involved in crashes. It was also found that risk perceptions and safety attitudes of e-bicyclists significantly impacted their behaviors in e-bicycle crashes. Wu et al.9 examined red-light running behaviors of e-bicyclists at three signalized intersections in Beijing using video cameras. It was found that age was significantly related to red-light running behaviors: young and middle-aged e-bicyclists were more prone to violate traffic rules. Besides, males were more likely to take risks than females at intersections. Bai et al.10 observed driving behaviors of ebicyclists at signalized intersection and concluded potentially dangerous conflict types between e-bicyclists and drivers. Hu et al.11 explored actors associated with e-bicyclists' injury severity. Age, road user category, traffic rule violation, crash mode, impact type, and vehicle type were found to related to injury severity. However, only hospital data were used and only two injury levels were considered. Bai et al.12 examined the driving behavior of e-bicyclists with the presence of mid-block bicycle lanes. Operating speed of e-bicycles, speed difference between bicycles and e-bicycles, volumes of e-bicycles, and the width of bike lanes were found to be related to e-bicyclist safety. Yang et al.13 presents a hazard-based duration approach to investigate riders' crossing behaviors at signalized intersections. Rider type, gender, waiting position, conformity tendency, and crossing traffic volume were identified to have significant effects on riders' waiting times and violation hazards. Zhang and Wu14 investigated the effect of sunshields on red-light infringement behavior of cyclists and e-bikers in the city of Hangzhou, China. Their results suggested that sunshields installed at intersections can reduce red-light infringement rates of cyclists and e-bikers on both sunny and cloudy days. Zhou et al. examined the relationship between e-bikes' passing rate and operating speed, using field data in Hangzhou. Average speed, 15 percentile speed, and speed variance were found as significant factors.15 Yang et al.16 investigated unsafe driving behaviors of ebicyclists in Suzhou, using a cross-sectional observation study. It was found that speeding, road rule violations and lack of helmet use were frequent unsafe behaviors for e-bicyclists, especially males. Wang et al.17 modeled for e-bicyclists, especially males. Wang et al.17 modeled faulty behaviors among e-bike-related fatal crashes in China. Pre-crash behaviors, bike lane and median type, older e-bike rider, heavy good vehicle drivers, and built environment were found to be correlated with faulty behaviors of e-bike riders. Xu et al.18 examined spatial interdependence in e-bike choice using spatially autoregressive model. It was found that travelers were more likely to use e-bikes if their neighbors at the trip origin and destination also use e-bikes. Previous studies, mostly based on surveys and observational studies, have provided valuable information

for understanding e-bicyclist safety. However, most focused on specific unsafe driving behaviors. To our

knowledge, there still lacks a thorough crash modeling effort based on historical crash records of e-bicyclist. Thus, in this article, we will examine all possible factors related to injury severity of bicyclists. By modeling injury severity, factors associated with probability of ebicyclists getting different levels of injury outcomes can be explored. In doing so, safety engineers are able to develop safety countermeasures to reduce the occurrence of severe injuries based on such modeling technique.

Data description

Crash records between e-bicycle and motor vehicle were utilized for crash modeling. The crash records

were drawn from the crash database regularly maintained by the traffic crash treatment center of Guilin Police Department. Over 31,000 crashes involving about 60,900 individuals from the year 2008 to 2014 were allowed to be accessed. Of these, about 4000 crashes involved e-bicycles. The injury severity of each e-bicyclist involved in the crash is recorded on 4-point ordinal scale: (1) no injury, (2) no treatment injury, (3) treatment injury, and (4) fatal. For the study purpose, we use only e-bicycles crashes that involve a single motor vehicle and an e-bicycle. After checking data validity and consistency, totally 3814 available crash records between e-bicycles and motor vehicles were finally extracted for further analysis. e-bicyclist demographics, crash characteristics, road geometrics, and roadway environments were found to be correlated with e-bicyclist safety, per the literature. More specifically, gender,6 age,9 driving behaviors of ebicyclists, 10 crash pattern,11 impact type,11 vehicle type,11 speed,12 and width of lane12 were found as significant. Thus, these factors need to be considered for severity modeling. Moreover, according to Kim et al.,19 driver demographics, vehicle features, time effects, and land use were found as significant to bicyclists' injury severity. Since bicyclists and e-bicyclists are comparable to two-wheel non-motorized users, those factors also need to be considered. Thus, in general, factors related to e-bicyclists' demographics, driver demographics, vehicle features, crash types, road geometry, time, environment, and land use were extracted from the crash records. The descriptive statistics is showed in Table 1. According to Table 1, e-bicyclists aged from 25 to 54 years comprised 58.1% of the sample. In 21.0% of the crashes, e-bicyclists were found to be older than 55. There was a share difference for gender, that is, about 56.9% of the crash-involved e-bicyclists were males while 43.1% were females. Regarding driver characteristics, in 74.1% of the crashes, motor-vehicle drivers aged from 25 to 54 years are identified. Most crashes were observer for male driver (87.4%). Drivers with less than 3 years of driving

experience account for 21.8% of the total crashes, while experienced drivers with driving experiences more than 10 years account for 30.6%. In 4.0% of the crashes, drivers were found to commit drunk-driving offense. Passenger cars were mostly often involved in e-bike crashes (56.5%), followed by motorcycle (17.6%). Note that heavy trucks accounted for only 10.3% of the total crashes, but 20.8% of fatal crashes. About 69.9% of the crashes are side-impact crashes between e-bicycle and motor vehicle head-on and rearend crashes account for 11.6% and 10.5% of the crashes, respectively. In 58.1% of the crashes, motor vehicles were determined to be solely at fault, while in 19.1% of the crashes, e-bicycles were determined to be solely at fault. Although motor vehicle drivers were found to commit speeding offense in 3.6% of the crashes, 23.7% of them were fatal crashes. About 39.3% of the crashes occurred in motorized lanes, while 20.4% of the crashes occurred in non-motorized lanes. In 8.2% of the crashes, drivers or e-bicycle riders were found to escape from crash scene. About 71.4% of the crashes occurred when the ebicyclist was going straight and 15.3% when the vehicle was turning right. 91.7% of the crashes occurred on straight roads and 56.2% happened on asphalt roads. The number of crashes occurred within intersections is close to that in roadway sections. More than half of the crashes occurred on urban arterials (60.8%). 47.1% of the crashes occurred on roadways where motorized and non-motorized vehicles are traveling together. In 35.9% of the crashes, there were traffic line markings between motorized and non-motorized vehicles. Regarding land use characteristics, crashes mostly occurred within residential area (37.9%), followed by commercial area (13.2%). About 39.3% of the crashes occurred within 30%–50% developed area and 50%– 80% developed area accounted for 26.2% of the crashes. About 32.8% of the crashes occurred on weekends and holidays. 12.8% and 13.9% of the crashes

happened during morning and evening peak hours, respectively. Most crashes occurred on sunny days (63.4%) and dry roads (77.6%). 72.5% of the crashes occurred during daytime and 49.5% of the crashes occurred when the sight distance is more than 200 m.

Methodology

In this study, injury severity is treated as a response variable with four levels: 0=possible or no injury, 1=no treatment injury, 2=treatment injury, and 3=fatality. Since injury severity is ordinal, ordered logit/proportional odds models are considered instead of multinomial models, which ignore the ordering of categories.20 In the ordered logit model/proportional odds model, there is an observed

ordinal variable Y, as a function of another latent variable Y*, that is not measured. The continuous and unmeasured latent variable Y whose values determine what the observed ordinal variable Y equals. The specification of ordered logit model is as follows

$$Y_i^* = a^* X + \varepsilon_i \qquad (1)$$

where $Y^*$is a latent and continuous variable (dependent) measuring the ith observation, that is the injury everity of the e-bicyclist in the ith crash record; X is a vector of explanatory variables describing e-icyclists' demographics, driver demographics, vehicle features, crash types, road geometry, time, nvironment, and land use; $a^*$is a vector of unknown parameters which need to be estimated, that is the coefficients of explanatory variables; e_i is a random error term which is assumed to have a logistic distribution. The observed injury severity variable Y* is determined by the following model

Table 1. Descriptive statistics

Variables	Fatal injury	Treatment injury	No treatment injury	Possible/no injury	Total

Table 1. Continued

Variables	Fatal injury	Treatment injury	No treatment injury	Possible/no injury	Total

Table 1. Continued

Variables	Fatal injury	Treatment injury	No treatment injury	Possible/no injury	Total
Time					
0:00–6:59	15 (5.3%)	106 (37.5%)	90 (31.8%)	73 (25.4%)	283 (7.7%)
7:00–8:59	22 (4.7%)	132 (28.0%)	180 (38.1%)	138 (29.2%)	471 (12.8%)
9:00–11:59	31 (6.0%)	186 (36.0%)	162 (31.3%)	138 (26.7%)	517 (14.0%)
12:00–13:59	33 (6.1%)	148 (27.4%)	192 (35.5%)	168 (31.1%)	541 (14.7%)
14:00–16:59	31 (4.7%)	246 (37.6%)	216 (33.0%)	162 (24.7%)	655 (17.8%)
17:00–18:59	15 (2.9%)	162 (31.6%)	180 (35.1%)	156 (30.4%)	513 (13.9%)
19:00–23:59	35 (5.0%)	224 (31.9%)	240 (34.1%)	204 (29.0%)	703 (19.1%)
Environmental characteristics					
Weather					
Clear	117 (5.0%)	742 (31.8%)	792 (33.9%)	684 (29.3%)	2335 (63.4%)
Cloudy	22 (5.6%)	202 (35.4%)	198 (34.7%)	138 (24.2%)	570 (15.5%)
Other (fog, rain, etc.)	33 (4.2%)	260 (33.4%)	270 (34.7%)	216 (27.7%)	779 (21.1%)
Light					
Daylight	122 (4.6%)	838 (31.0%)	942 (35.3%)	780 (29.2%)	2672 (72.5%)
Dark-streetlight	31 (4.0%)	244 (31.8%)	258 (33.6%)	234 (30.5%)	767 (20.8%)
Darkness-streetlight	29 (11.8%)	132 (53.9%)	60 (24.5%)	24 (9.8%)	245 (6.7%)
Road surface					
Dry	139 (4.9%)	968 (33.9%)	942 (32.9%)	810 (28.3%)	2859 (77.6%)
Other	43 (5.2%)	236 (28.6%)	318 (38.5%)	228 (27.6%)	825 (22.4%)
Visibility					
<50 m	33 (9.4%)	150 (42.7%)	120 (34.2%)	48 (13.7%)	351 (9.5%)
50–100 m	37 (4.7%)	306 (38.9%)	264 (33.5%)	180 (22.9%)	787 (21.4%)
100–200 m	28 (3.9%)	216 (29.8%)	258 (35.6%)	222 (30.7%)	724 (19.7%)
>200 m	84 (4.6%)	532 (29.2%)	618 (33.9%)	588 (32.3%)	1822 (49.5%)
Total	182 (4.9%)	1204 (32.7%)	1260 (34.2%)	1038 (28.2%)	3684

$$Y_i = \begin{cases} 0 \; if \; -\infty < Y_i^* < \omega_1 & possible \; and \; no \; injury \\ 1 \; if \; \omega_1 < Y_i^* < \omega_2 & no \; treatment \; injury \\ 2 \; if \; \omega_2 < Y_i^* < \omega_3 & treatment \; injury \\ 3 \; if \; Y_i^* > \omega_3 & fatality \end{cases} \quad (2)$$

where vk is an unknown threshold to be estimated along with parameter a, aexplains how explanatory variables affect the underlying injury severity level

$$\omega_k < Y_n^* < \omega_{k+1} \Rightarrow \omega_k < a^*X + \in \; \leq \omega_{k+1}$$
$$\Leftrightarrow \omega_k - a^*X < \in \; \leq \omega_{k+1} - a^*X \quad (3)$$

Since e is assumed to obey logistic distribution in ordered logit model, the probability of the response variable at level k can be computed as

$$P(Y_i = k) = P(\omega_k < Y_i^* \leq \omega_{k+1})$$
$$= 1 - P(Y_i^* > \omega_{k+1}) - 1 + P(Y_i^* > \omega_k) \quad (4)$$

where

$$P(Y_i^* > \omega_k) = \frac{\exp(aX'_i - k_j)}{1 + \exp(aX'_i - k_j)} \quad k = 1,2,3 \quad (5)$$

For the ordered logit model, the relationship between any pairs of outcome categories is assumed to be equal. In other words, the thresholds have to be fixed for all explanatory variables. If this assumption (i.e. the parallel line assumption) is sometimes violated by some explanatory variables that they may have different effects on thresholds with other variables, the ordered logit model could result in biased estimates.21 To address this, a generalized ordered logit/partial proportional odds model can be used instead that relax the parallel line assumption. Moreover, it is more parsimonious than traditional multinomial logit/probit models that are often suffer from independence of irrelevant alternative (IIA) issues.20 The probability of Y* larger than a specific threshold can be specified as

$$P(Y_i^* > \omega_k) = \frac{\exp(X'_{1i}b_1 + X'_{2i}b_{2j} - k_j)}{1 + \exp(X'_{1i}b_1 + X'_{2i}b_{2j} - k_j)} \quad k = 1,2,3$$
$$(6)$$

where b1 is a vector of parameters of variables that follow the parallel line assumption and is associated (Xli), and b2j is a vector of parameters of variables that vary across different severity levels (X2i). If no variables were found violating the parallel line assumption, the model will degenerate to the ordinary ordered logit model (i.e.equations (1)–(5)) and all variables will have constant coefficients across all injury levels. The probability of injury severity has a closed-form expression20 and the log-likelihood function can be expressed by

$$\ln(L) = \sum_{n=1}^{N} \sum_{k=1}^{3} K_{nk} \ln P(Y_i^* > \omega_k) \quad (7)$$

where ln(L) is the log-likelihood function, Knk is equal to 1 if crash n results in severity level k and 0 otherwise, and N is the number of crashes. Variable coefficients were obtained by maximize the likelihood function, given the observations. The marginal effect of a variable indicates how the factor affects the response variable on the underlying scale. For continuous variables, marginal effects can

be obtained by calculating derivatives. For dummy variables, a difference rather than the derivative is calculated. The goodness of fit for the partial proportional odds model is measured by the likelihood ratio index. The likelihood ratio index can be calculated by

$$R^2 = 1 - \left[\frac{\ln L_a}{\ln L_0}\right] \qquad (8)$$

where ln La is the log-likelihood with all predictors included in the model (at convergence); ln L0 is the loglikelihood value of the models containing only intercept (at constants); The likelihood ratio is improved when the value of index increases from 0 to 1.22 Akaike information criterion (AIC) can be utilized to evaluate model's performance. The specification of AIC can be written as

$$AIC = -2 \ln L_a + 2P \qquad (9)$$

where P is the number of parameters estimated.

Results

Table 2 shows the estimated e-bicyclist injury severity model, including the parameter estimates, standard errors, and level of significance. According to modeling results, a number of factors have been identified to be significantly associated with injury severity sustained by e-bicyclists. A series of Wald tests were applied to determine the validity of parallel line assumption.20 Variables with p value less than 0.05 are considered to have heterogeneous effects across different severity levels. Table 2 shows that all variables have p values larger than 0.05, indicating that no variable included in the final model violates the parallel line assumption. In this case, the generalized ordered logit model provides the same estimates with an ordinary ordered logit model. Despite of that, the generalized ordered logit model was still considered as superior than the ordered logit model, because it was able to detect the existence of heterogeneity effects across observations (no such existencewas found in this study). Moreover, considering injury severity as an ordinal instead of nominal variable is intuitively a more reasonable model choice, since there is a clear ordering from non-injury to fatality Thus, the generalized ordered logit model is a better choice than traditional multinomial models, in terms of modeling crash severity.

e-bicyclist characteristics

e-bicyclists aged 55 years and over are more prone to be injured than younger e-bicyclists. This result is consistent with other studies that older adults are more likely to suffer fatal injuries in bicycle crashes.23–25 However, many unobserved variables could be correlated with age.26 For example, reaction time, physical fragility, and bone density could also contribute to higher injury probability. The result shows that males are associated with lower injury severity. The reason, however, could not be revealed based on data. A possible reason could be the difference in physical fragility between male and female.

Driver characteristics

When drivers are intoxicated, the probabilities of ebicyclists' injuries largely increase. Similar results can be found in Noland and Quddus'27 research, they found that drinking drivers had significant associations with bicycle injury severity. Drivers with less than 2 years of experience are more likely to be severely injured. Lack of experience could be a reason: inexperienced drivers could be more likely to mistakenly conduct improper maneuvers in emergency conditions.

Vehicle characteristics

The vehicle type variables were also found to be significant correlated to e-bicyclists' injury severity. Unsurprisingly, heavy trucks could be expected to be related to higher injury severity. The similar result is found by McCarthy and Gilbert28 that the heavy trucks were more likely to be related to fatal bicycle crashes, since heavy trucks have greater momentum than passenger car. Motorcycles are more likely to be involved in severe e-bicycle crashes. The reason could be due to frequent speeding offense of motorcycles in China, as claimed by Guilin Police.

Crash characteristics

Head-on crashes have a positive relationship with the probability of severely injured in crashes. When considering fault, Table 1 show that e-bicyclists are found jointly at fault most of the time. This result

is consistent with Kim et al.'s19 study that cyclists are more likely to commit faults than motorists. The model results from Table 2 indicate that e-bicyclists are more likely to be severely injured when they are solely at fault. Crashes with e-bicyclists at fault often occur at motorized lanes, probably resulting in more severe injuries. When driving on motorized lanes, e-bicyclists have higher risk of being injured. e-bicycle riders were found to frequently drive in motorized lanes, increasing their exposure of being crashed by motor vehicles.

Table 2. Parameter estimation of generalized ordered logit model.

	Estimates	Standard deviation	Significance	Wald tests (p value)
Threshold parameters				
Fatal injury	-0.439	0.199	0.027	
Treatment injury	1.572	0.211	0.000	
No treatment injury	2.895	0.513	0.008	
e-bicyclist characteristics				
e-bicyclist age 55 + years	1.523	0.545	0.005	0.2123
e-bicyclist is female	0.249	0.110	0.023	0.3476
Driver characteristics				
Driver is intoxicated	1.429	0.315	0.000	0.4511
Driver years <3	0.525	0.231	0.033	0.8781
Vehicle characteristics				
Motorcycle	0.870	0.221	0.004	0.2310
Heavy truck	2.703	0.268	0.000	0.5623
Crash characteristics				
Head-on crash	0.543	0.207	0.047	0.5521
e-Bicyclist at fault	1.782	0.188	0.000	0.3395
Speeding	0.191	0.083	0.032	0.1233
Crash in motorized lanes	1.186	0.287	0.000	0.1587
Behavior characteristics				
e-bicyclist turning left	0.988	0.404	0.014	0.4368
e-bicyclist crossing the road	1.692	0.497	0.001	0.5629
Driver turning right	1.225	0.205	0.000	0.7731
Geometry characteristics				
Signal intersection	0.304	0.123	0.014	0.2361
Curved road	0.727	0.224	0.001	0.1137
Rural highways	1.254	0.330	0.000	0.0945
No. of traffic lanes = 1	0.279	0.068	0.031	0.2466
Trees separation between motor vehicle and e-bicycle	1.470	0.560	0.009	0.4821
Two-way divided by trees separation	-0.700	0.231	0.002	0.2264
Two-way divided by barriers	-0.855	0.322	0.008	0.0742
Temporal characteristics				
Weekday	0.434	0.148	0.003	0.5366
p.m. peak	-0.643	0.297	0.030	0.8615
Land characteristics				
Development	-0.462	0.123	0.000	0.4672
Residential area	-0.716	0.273	0.009	0.8463
Industrial area	0.543	0.207	0.047	0.5923
Log-likelihood at convergence	-3887.1			
Log-likelihood at constant	-5592.6			
Pseudo R^2	0.315			
AIC	7830.2			

AIC Akaike information criterion.

When speeding offense is found in e-bicycle crashes, the injury severity of e-bicyclists significantly increased. This finding is reasonable since, intuitively, larger speed could result in higher impact force, causing more severe injuries to e-bicyclists.

Behavior characteristics

e-bicyclists are more likely to be severely injured when they are making left turns or crossing streets. When making such moves, e-bicyclists have to pass motorized lanes, increasing their exposure. Meanwhile, drivers could underestimate the speed of e-bicycles, resulting in severe crashes. When e-bicycle riders make right turns, their injury risk also increases. This could be partly attributed to the right-turn-on-red rules. Drivers could ignore the presence of e-bicycle riders when they make right turns on red. Another possible reason could be that the right-turn radius of intersections is designed to be relatively larger in China, causing relatively higher turning speed. In this case, e-bicyclists could underestimate the operating speed of vehicles. Moreover, the difference of radius between inner wheels could be another factor. Especially for large trucks, drivers could consider that they successfully overtake e-bicycles, after the front wheels of vehicles passing e-bicycles. However, the rear wheel could still crush e-bicyclists due to the difference of radius between inner wheels.

Geometry characteristics

Signalized intersections are correlated with increased risk of high injury severity of e-bicyclists. Red-light running is a frequent illegal behavior conducted by e-bicycle riders, which could significantly increase their risk. Ebicyclists are more likely to be injured when they are driving on curves. The increased maneuvering difficulty and reduced vision on curves could be a factor. Rural highways are correlated with higher injury severity of ebicycle riders. Rural highways are set to have relatively higher speed limits than urban roads. Moreover, lighting conditions in rural highways could be worse than urban highways. Single-lanes are correlated with higher probability of severe injuries. The possible reason could be due to the limited room increasing potential conflicts between e-bicycles and motor vehicles. With the presence of trees separation between motorized and non-motorized vehicles, severe crashes are more likely to occur. With trees separation, drivers could be less cautious to e-bicyclists, increasing traffic risk when e-bicyclists are crossing streets. To tackle this, deploying

warning signs at the mid-block openings could be a viable option. Two-way divided roadways are associated with higher probability of low injury severity of e-bicyclists. It could be that e-bicyclists are less likely to driver in opposite directions on divided roads which leads to fewer head-on crashes. Barriers are correlated with less severe injuries, compared to trees separation. With barriers, both e-bicycle riders and drivers have better sights and visions, when they make turns or crossing streets. Temporal characteristics e-bicyclists are more likely to be severely injured on weekdays. This result is contradictory with the previous research in other countries that weekend crashes were found to result in a higher probability of increased injury severity.22,24 e-bicycles are extensively used for daily commuting in China. Thus, e-bicycle riders could have higher exposure during weekdays, which could be a potential reason. e-bicycle riders were less likely to be severely injured during evening peak hours (17:00–19:00). Thanks to high traffic volume, motor vehicles move slowly during this period, probably resulting in lower pre-crash speed. Land use characteristics In this article, a land development intensity variable was defined as an index that ranges from 0 to 1, with 1 indicating high intensity of development and 0 indicating low intensity of development. The model results show that land development intensity is negatively associated with the injury severity of e-bicyclists. Within highly-developed area, traffic volume is relatively large, possibly resulting in low vehicle speed. Moreover, in such area, walking and public transit facilities are also well developed, lowering the share of e-bicycle usage. Commercial areas are associated with the decreased injury severity of e-bicycle riders. This is presumably due to well-developed walking and public transportation facilities within such area, such as quality streetlights roadway markings and dedicated e-bike facilities, lowering e-bicycle usage. Residential area is associated with the decreased injury severity of e-bicyclists. It could be the reason that

the speed limit within such area is set to be relatively low due to the high population and building density.

Another possible reason could be drives' compensatory behaviors with the anticipation of encountering nonmotorists (e.g. pedestrians and cyclists) within such area. Industrial area is linked to high injury severity. Based on our observations, these areas lack of traffic facilities for non-motorists, which could be a possible reason. Since commercial large trucks are predominant in this area, they could also be associated with increased injury severity of e-bicyclists.

Conclusion

According to results, factors associated with increased injury severity of e-bicyclists include older e-bicyclists, female e-bicyclists, intoxicated drivers, inexperienced drivers, motorcycles, heavy truck involved, e-bicyclist at fault, speeding, motorway, e-bicyclist turn left, ebicyclist cross the road, driver turn right, signalized intersections, curved road, industrial area, weekday, head-on crashes, and tree separation. Variables correlated with the decreased injury severity of e-bicyclists are two-way divided roadways with tree separation or barriers, peak hours, and highly-developed area including commercial area and residential area.

Based on results, older e-bicyclists, female e-bicyclists, and inexperienced drivers are specific age groups

that deserve in-depth research on their driving behaviors when encountering each other. e-bicycle entry pass could be considered to limit older people over certain age. e-bicyclists should be more cautious when

making left turns and crossing streets. However, drivers need to pay more attention to e-bicyclist when they are making right turns. Safety campaigns may help to improve their safety awareness. Since there is no license and insurance required for e-bicyclists, e-bicyclists often violate traffic rules without paying much cost. Currently in some cities in China, registration and insurance policy has been Wang et al. 9 launched for e-bicycles. The effects of such policies in improving e-bicycle safety will be examined in future. e-bicyclists could be at high risk in low-developed area, curve roads, and signalized intersections. Thus, it is recommended that geometric design and traffic control in those areas should consider e-bicycle safety, in terms of visibility and maneuverability. Possible interventions could

include bike boxes, cycle tracks, shared roadway markings, signals for cyclists, and colored bicycle lanes.1 Especially, signs should be deployed at median-openings on roadways with tree separations to increase cyclist visibility. When driving in darkness without streetlights, drivers should be cautious while ebicyclists should wear reflective cloth and keep their lights on. Moreover, speeding is a serious safety concern for e-bicyclists, especially in low-developed area. Thus, certain safety countermeasures should be deployed, such as speed bumps, flashing lights, and warning monitors. More importantly, this article suggests some interesting preliminary findings related to crash mechanism. When heavy trucks and motorcycles are involved, ebicyclists have increased injury propensity. Thus, the crash mechanism between those parties needs to be further explored, especially from kinetic and kinematic perspectives. In addition, head-on crashes is the only crash type correlated with e-bicyclists' increased injury severity. The major difference among head-on and other crash types (e.g. angle) for e-bicyclists in terms of kinematic and kinetic could be of particular interest. Moreover, tree separation for non-motorists increases injury severity of e-bicyclists. It is worthwhile investigating other separation treatments that could better protect e-bicyclists when crashes occur. It should be recognized here that this article has some limitations: (1) police-reported crash data often suffers from data accuracy, causing biased model estimates. However, in this study, all efforts have been undertaken to improve data quality; (2) some significant factors may not be considered in this study, such as traffic volume and speed. Those factors need to be incorporated in future studies. In general, the finding of this article provides valuable information for understanding e-bicyclist safety and developing safety countermeasure and policies for e-bicyclists' safety improvement. Moreover, some interesting and important research topics related to crash mechanism were also suggested.

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