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Influence of familiarity with traffic regulations on delivery riders' e-bike crashes and helmet use: Two mediator ordered logit models

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ABSTRACT

Micro-mobility vehicles such as electric bicycles, or e-bikes, are becoming one of the essential transportation modes in metropolitan areas, and most deliveries in large cities are dependent on them. Due to the e-bike's popularity and vulnerability, e-bike crash occurrence has become a major traffic safety problem in many cities across the world; finding the most important human factors affecting e-bike safety has thus been an important recent issue in traffic safety analysis. Since delivery riders are a key group of e-bike users, and since helmet use plays a crucial role in reducing the severity of a crash, this study conducted a city-wide online survey to analyze the helmet usage of 6,941 delivery riders in Shanghai, China. To determine the in-depth mechanisms influencing helmet use and e-bike crash occurrence, including the direct and indirect effects of the relevant factors, two mediator ordered logistic regression models were employed. The mediator ordered logistic model was compared with the traditional logistic regression model, and was found to be superior for modeling indirect as well as direct influencing factors. Results indicate that riders' familiarity with traffic regulations (FTR) is an extremely important variable mediating between the independent variables of riders' educational level and age, and the dependent variables of helmet use and e-bike crashes. Improving riders' FTR can consequently increase helmet use and decrease crash occurrence. Authorities can apply these findings to develop appropriate countermeasures, particularly in legislation and rider training, to improve e-bike safety.

1. Introduction

Electric bicycles, or e-bikes, are among the fastest growing transportation modes in the world due to their high speed, ease of travel, and low cost: they move at 15–20 km/hr, are more flexible than other motorized vehicles in urban traffic jams, and average ¥1,960 (US $280) in China. Their increased presence in western countries has been shown to reduce the number of car trips (Fyhri & Fearnley, 2015; Haustein and Møller, 2016). In China, by the end of 2019, the total number of registered two wheelers reached 700 million, of which>40% were e-bikes (Bicycle Helmet Safety Institute, 2019). This proportion is not surprising as e-bikes are often favored by business couriers (Chung et al., 2014). Of the 3 million couriers in China in 2018, Shanghai ranked among the top three cities in number of couriers, or delivery drivers, and a recent study found that approximately 65% of Shanghai delivery drivers use e-bikes (Zheng et al., 2019). In Shanghai in 2021, there are>13 major delivery companies and the population of e-bike delivery rider was as high as 90,000 (Traffic Management Bureau of the Public Security Ministry, 2021).

The current popularity of e-bikes means that they are involved in a greater number of traffic crashes than before (An et al., 2013; Fyhri et al., 2019). In the delivery industry, efficiency is one of the most important demands. Delivery riders are prone to violate traffic laws in order to reach their destinations faster; they have thus been found responsible for many e-bike crashes (Chung et al., 2014; Yu et al., 2018). The quantity and arrangement of the commodities they commonly carry may further detract from their safety. Fig. 1 exhibits the inherent complexity of the driving conditions of two e-bike delivery riders in Shanghai.

E-bike riders are also vulnerable road users. Because their crashes

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often result in personal injury, essential e-bike safety research includes crash severity as well as frequency (Tang et al., 2021; Useche et al., 2019). A considerable volume of research has shown that not wearing a helmet can lead to severe injuries after a crash (Kasm et al., 2019; Wang et al., 2012). In 2020 the Chinese government instituted the "One Helmet, One Belt" policy to encourage automobile passengers to use seatbelts and the riders of e-bikes, motorcycles, and bicycles to wear helmets. However, compliance is not mandatory in many areas and promotion of the policy is still insufficient, so the overall helmet usage rate is not high. The delivery industry in China has a fairly good record of helmet use, but it is a major user of e-bikes and its record could be improved, increasing not only the safety of its couriers but also serving to promote helmet use in the general population.

Previous studies have shown that age, educational level, and the familiarity with traffic regulations (FTR) were directly connected with e-bike safety (Haustein and Møller, 2016; Fyhri et al., 2019; Useche et al., 2019). Although helmet use is not currently among the traffic regulations universally mandated in China, research suggests it is reasonable to hypothesize that FTR may link to a general awareness of safety that may, in turn, relate to helmet use; that is, they may correlate indirectly. For example, stress can directly affect driving behavior, but sometimes the influence can be indirect, such as through the mediating variable of inattention (Chen et al., 2019).

The expanded use of e-bikes has contributed to the mixed traffic environment that has been shown to reduce road safety overall, a problem that is becoming increasingly severe in large cities (Haustein and Møller, 2016; Popovich et al., 2014). The risks are especially high for frequent and vulnerable road users such as delivery riders, yet, despite their conditions and heavy exposure, delivery riders have been insufficiently studied. The effects on helmet use of age, educational level, and FTR have also not been studied. Targeted research on the factors affecting delivery riders' e-bike crash occurrence and their helmet use is urgent. It can help the delivery industry, and the broader public, understand the full benefits of helmet use, and can help regulators design traffic safety education specifically for e-bike users. Knowing the influence of couriers' age and educational level may suggest certain interventions, but increasing their FTR may have particular impact. Instruction on traffic regulations is one of the main content areas of safety education programs, and it can be improved. As found in other studies on driver education and crashes, providing targeted safety education countermeasures can promote e-bike safety (Lawson et al., 2013; Safer Cycling, 2019; Yang et al., 2018).

To increase understanding of how these different factors and their interdependencies influence both e-bike crashes and helmet use, this study conducted a city-wide self-reported online survey to examine courier e-bike usage in Shanghai. Human factors and e-bike crash frequency were collected from 6,941 delivery riders. Self-reporting has its drawbacks, but was deemed the best data collection method for this study. Our primary aim is to improve e-bike safety legislation and training, and the kind of behavioral characteristics most susceptible to educational intervention may be best collected by subjective self-reporting. As traditional analysis methods cannot explain the indirect relationships we expected to find, two mediator models were built using educational level, age, and FTR as independent variables; the dependent variable in one of the models was e-bike crash occurrence, and was helmet use in the second model. FTR was considered as a potential mediating variable, that is, a bridge between the relationships of the other two independent variables and the dependent variable, which can help us to find a practical solution to increase helmet use.

2. Literature review

Many researchers have studied the socio-demographics of e-bike riders using traditional analysis methods such as descriptive statistics, correlation, and regression analysis. A cross-sectional study of 824 Chinese delivery riders showed that>90% of the sample were male and 72.4% were in the age range of 26–35 (Zheng et al., 2019). A self-reported survey found that 40% of Chinese e-cyclists had only received basic education in high school or below (Yang et al., 2018), whereas a California study identified the median age of e-cyclists at 35, and almost 80.5% had educational levels of high school or higher (Popovich et al., 2014). A descriptive statistics study in Shanghai showed that age made no significant difference in crash risk (An et al., 2013), while Fyhri et al. (2019) found that crash risk increased with younger men. Using a one-way ANOVA analysis, Akaateba et al. (2015) found that higher educational levels negatively correlated with speeding violations. In contrast, a study using a logistic regression model showed that highly educated drivers had a greater number of traffic violations (Tseng, 2013). Haustein and Møller (2016) found that differences in cycling regulations are likely contributing to such contradictory e-bike risk results. Yang et al. (2018) found a significant negative relationship between strict regulations and e-bikers' risky behaviors, and suggested that employing stricter rules might reduce those behaviors.

If regulatory differences are causing some of the contradictory results, it could be due to local differences in regulations, but it could also be due to the complexity of the relationships among influencing factors. Ajzen's theory of planned behavior (TPB) proposes that attitudes toward behaviors and perceived behavioral norms can affect behavioral intention, which Ajzen (1991) defines as the perceived degree of control over the behavior; and intention can, in turn, affect actual behavior. Various traffic safety researchers have used TPB to relate these individual differences to driving behavior and crash risk (Akaateba et al., 2015), but often the relationships are not direct, but indirect.

Mediating variables are often necessary in the social sciences to more

(a) **Package delivery** (b) **Food delivery**

Fig. 1. Delivery riders using e-bikes.

clearly explain the effects, especially indirect effects, of certain factors. A mediating effect refers to the process by which a predictor affects a dependent variable through a mediator. That is, one independent variable affects another, the mediating variable, which, in turn, affects the dependent variable. A mediator model can be built to seek the mechanisms that underlie observed relationships between independent and dependent variables (Preacher & Kelley, 2011). The model thus analyzes the mediating effects by explaining and integrating the relationships among multiple independent variables (MacKinnon, 2008). Because traditional analysis only considers the direct influence of independent variables on the dependent variables, mediation analysis obtains more in-depth results and thereby makes progress in methodology (Yzerbyt, 2005). Mediation analysis has been widely utilized in traffic safety research. It has been used to study various road users, including automobile drivers (Kim and Chung, 2019; Husain et al., 2019), pedestrians (Xu et al., 2018; Meng et al., 2020), bicyclists (Han et al., 2017), and motorcycle riders (Nguyen-Phuoc et al., 2020). To our knowledge, Tang et al. (2021) is the only mediation analysis of the factors that influence e-bike riders' behavior. Moreover, previous e-bike safety studies did not take category variables as the research object, the mediator ordered logit model can capture some deep factors affecting driver helmet use and accident occurrence.

Helmet use by e-bike riders has been similarly lacking. In an analysis by Kasm et al. (2019), helmet use by cyclists was shown to reduce the fatality rate by up to 60%. No previous studies have examined the direct influence of education or age on helmet use, yet these two human factor variables may affect helmet use through the mediator of familiarity with traffic regulations (FTR). Previous studies on age have demonstrated that older people are more familiar with regulations than younger people (Nordfjærn et al., 2010), and other research suggests that FTR may positively influence e-bike riders' helmet use. Using ordered logistic analysis, Wang et al. (2012) found that e-bike riders with weak law and safety awareness exhibited multiple dangerous riding behaviors. Valero-Mora et al. (2020) conducted an online survey of 5,918 respondents in 18 countries on bicycle helmet law and found that although both Australia and Argentina have mandatory helmet laws, Australian respondents exhibited over twice the level of awareness of the helmet law (91%) than Argentinians (45%); the Australians' helmet wearing proportion was 75.6% in contrast to 37.5% of Argentinians.

Likewise, FTR may reduce e-bike crashes. A study using a structural equation model demonstrated that enhancing road users' awareness of regulations improved their driving behavior and reduced the number of crashes in which they were involved (Useche et al., 2019). An empirical study using ordered logistic regression (OLR) and principal component analysis (PCA) indicated that cyclists who were familiar with traffic rules were involved in a relatively low number of crashes (Lawson et al., 2013).

Due to the various correlations of age and educational level with regulation familiarity, and regulation familiarity with helmet use and with e-bike crashes, in conjunction with the related findings in psychological theory, it can be hypothesized that FTR may play a mediating role in the influence of both educational level and age factors with respect to helmet use and e-bike crashes.

3. Methods

3.1. Research design

The research design of this study was to conduct a cross-sectional survey of Shanghai e-bike couriers using a questionnaire to investigate targeted human factors in the couriers' crashes and helmet use. The collected data were used to analyze the direct and indirect influences of each of the factors, specifically age, educational level, and familiarity with traffic regulations, on helmet use and crashes. To determine these influences and identify mediator effects, two mediator ordered logistic regression models were developed, one for each of the dependent variables.

3.2. Survey instrument

The survey instrument is a questionnaire that contains a core set of items asked of delivery riders in order to provide information on demographic information, attitudes, and behavioral trends related to e-bike use.

The survey measured three overall areas, as follows:

1) Work-related e-bike crash frequency during their careers as delivery riders;
2) Helmet use: helmet ownership, frequency of helmet use while working, and if applicable, main reasons for not wearing a helmet;
3) Other human factors: gender, age, educational level, and familiarity with traffic regulations (FTR).

All data were self-reported and therefore subjective. Additionally, reported data relied on participants' memory, such as their recollection of how often they wore helmets, and how often they were involved in work-related e-bike crashes. Despite its disadvantages, self-reported data was appropriate for collecting the behavioral characteristics of interest. The questionnaire took the couriers an average of five minutes to complete. Their personal information is kept confidential and answers are anonymized.

3.3. Sampling and data collection

Due to the large number of delivery rider population (>90,000) and delivery companies (13 major delivery companies and a large number of small companies) in Shanghai, the online survey with a probability cluster sampling was chosen in this study.

Before disseminating the survey, we piloted the survey's usability to confirm that it could be easily accessed and completed online via the survey link. Together with the Shanghai Traffic Police Department, we first extracted several representative large delivery companies from Shanghai delivery companies list. Then we administered an online survey to the delivery riders from these delivery companies using the quick response code link (Fig. 2), which was shared in their online groups/communities setting up for managing these riders. The data collection period was approximately two months, from March 30 to June 8 in 2019.

Cluster sampling is usually conducted when the divided clusters are similar to each other whereas the subjects within each cluster have great heterogeneity (Jackson, 2011). In this study, the delivery rider population is first divided into mutually primary sampling units (PSU) according to the delivery companies list. Then several representative delivery companies are selected to obtain the secondary sampling units (SSU), and investigated delivery riders in the SSUs. Moreover, the online survey is time-efficient and cost-efficient probability design for large geographical areas, and is easy to implement. The online survey with a probability cluster sampling method is a proper sampling method for this study.

About 7,000 questionnaires were obtained in this study, of which only a few contained missing data. These were discarded as invalid responses, resulting in a total of 6,941 valid questionnaires. The usable returned rate was about 99.16%.

3.4. Data analysis

When a dependent variable is a hierarchical variable of multiple categories, the ordered logistic model can be used for regression analysis (Train, 2003). Therefore, to find the in-depth relationships between the independent variables influencing the reported e-bike crashes and helmet use, we established two mediator ordered logistic regression models. The models were developed using M−plus 7.4 for analysis of the

Fig. 2. Delivery riders at a questionnaire site.

dependent variables: e-bike traffic crashes and helmet use. The mean- and variance-corrected weighted least squares (WLSMV) method was chosen to estimate the models. WLSMV is a robust estimator that does not assume normally distributed variables, and provides the best option for modelling categorical or ordered data (Brown, 2015). This method also provides the root mean square error of approximation (RMSEA), comparative fit index (CFI), Tuck-Lewis index (TLI), and weighted root mean square residual (WRMR) needed to effectively evaluate the goodness of fit (Bentler and Bonett, 1980).

The frequency of helmet use was categorized into three levels and coded as 1 = Never, 2 = Occasionally, 3 = Frequently. E-bike crash occurrence was categorized into four levels of increasing frequency and coded as 1 = None, 2 = 1–3 times, 3 = 4–6 times, 4 = >6 times. Age, educational level, and FTR were treated as categorical variables.

For both models, we suppose that the dependent variable Y has j levels and the independent variable is X, in which case there are j-1 ordered logistic equations in the model. When $Y > j$ $(0 < j \leq J-1)$, the traditional ordered logistic regression model is as follows:

$$LogitP(Y>j|X) = \ln\frac{P(Y>j|X)}{1-P(Y>j|X)} = \alpha_j + \beta X_m + \mathrm{e} \tag{1}$$

For each j, *Logit P* is the linear function of the independent variable, m in X_m represents the category of variable X, and α_j and β are parameters to be estimated. Both ordered logistic regression models obey the proportional odds hypothesis; that is, the regression coefficient $\beta$of independent variable X_m is independent of j (Mccullagh, 1980).

In this study, the ordered logistic regression is extended to the analysis of the mediating effect, so the mediator model is expressed as:

$$Y' = LogitP(Y>j|X) = ln\frac{P(Y>j|X)}{1-P(Y>j|X)} = i_{1j} + c_m X_m + e_1 \tag{2}$$

$$Y'' = LogitP\ (Y>j|M,X) = ln\frac{P(Y>j|M,X)}{1-P(Y>j|M,X)} = i_{2j} + c_m' X_m + bM + \mathrm{e}_Y \tag{3}$$

$$M = i_3 + aX_m + \mathrm{e}_M \tag{4}$$

c_m quantifies the total effect of X_m (educational level or age) on Y (e-bike crash occurrence or helmet use); c_m' quantifies the direct effect of X on Y; a quantifies the direct effect of X on M (familiarity with traffic regulations); b quantifies the direct effect of M on Y; and a × bis the indirect effect of X on Y through M. In eqs. (2) and (3), since c_m, b, and c' cannot change due to the different values of j, the size of the mediating effect is not affected by the number of classes of the dependent variable Y. Because the index of the mediator is a_1b_1, if all paths are significant, then $c_m = c_m' + a_1b_1$ (Preacher & Kelley, 2011).

In this study, age (A) and educational level (E) may have direct effects on crashes (Z) and helmet use (W), and they may also have indirect mediated effects through familiarity with regulations (M). When all variables are considered, then the total effect of education (E) on each of the dependent variables (e-bike crash occurrence or helmet use) is$c_E = c'_E + a_1b_1$ (c'_E means the direct effect of E on Z/W; a_1 quantifies the direct effect of E on M; b_1 quantifies the direct effect of M on Z/W; a_1b_1 means the indirect mediated effect of E on Z/W through M). The total effect of age (A) on each of the dependent variables is $c_A = c'_A + a_2b_2$ (c'_A means the direct effect of A on Z/W;a_2 quantifies the direct effect of A on M; b_2 quantifies the direct effect of M on Z/W; a_2b_2 means the indirect mediated effect of A on Z/W through M). Finally, the total effect of education (E) and age (A) on each of the dependent variables is $c_{\text{total}} = c_E + c_A$.

4. Results

4.1. Descriptive results

Table 1 shows most of the obtained characteristics of the sampled delivery riders. It will be noted that gender is not included. The sample was found to be 97% male, and although it was heavily biased towards male riders, the gender balance is not unrepresentative of the industry. Consequently, this study will not undertake an in-depth analysis of the gender dimension.

Their ages ranged mainly from 26 to 40, relatively young within the general population. This finding is generally consistent with previous research indicating that 72.4% of delivery riders are between 26 and 35 (Zheng et al., 2019).

The subjects' educational level was relatively low, with most having only received basic middle school education, that is, finishing school at approximately 15 years old. Only about 9% of the respondents had higher education such as a bachelor's degree. This concurs with Zheng (2019), who also found similar results in a sample of delivery drivers in China, though in a survey of California e-cyclists in general, that is, not only delivery riders, Popovich et al. (2014) found that almost 80.5% had a high school education or higher.

Likely due to strict industry rules, 90.6% of delivery riders said they frequently wear helmets while working, while only 9.4% of respondents occasionally or never wear them. The main reasons for reluctance to wear helmets were that they felt stuffy, too heavy, and inconvenient to carry. Almost 62% of respondents were somewhat familiar or very familiar with regulations.

Table 1
Characteristics Analysis of E-bike Delivery Riders (n = 6,941).

Variables	Category	Number of observations in population	%
Age	<25 Years	1,797	25.9%
	26–30 Years	2,434	35.1%
	31–40 Years	2,157	31.1%
	>41 Years	553	8.0%
Educational level	Middle school	2,777	40.0%
	High school	3,547	51.1%
	Bachelor's/Junior college	617	8.9%
Familiarity with traffic regulations (FTR)	Totally unfamiliar	186	2.7%
	Somewhat unfamiliar	204	2.9%
	Neither unfamiliar nor familiar	2,256	32.5%
	Somewhat familiar	1,522	21.9%
	Very familiar	2,773	39.9%
Helmet ownership	Own	6,666	96.0%
	Do not own	275	4.0%
Helmet use	Never	83	1.2%
	Occasionally	567	8.2%
	Frequently	6,291	90.6%
Main reasons for not wearing a helmet	Stuffy	5,685	81.9%
	Heavy	3,706	53.4%
	Ugly	896	12.9%
	Inconvenient	2,007	28.9%
	Expensive	321	4.6%
	Not fashionable	492	7.1%
	Disagree with safety benefit	636	9.2%
	Other	440	6.3%
E-bike crash occurrence	None	5,349	77.1%
	1–3 times	1,498	21.6%
	4–6 times	49	0.7%
	> 6 times	45	0.6%

Over 77% of surveyed delivery riders reported never having been involved in an e-bike crash while working. That is, more than a fifth of the sample had experienced one or more work-related e-bike crash, while only 1.4% had experienced four or more work-related e-bike crashes. This result is higher than previous studies, which found that the prevalence of electric bike/moped-related road traffic injuries among the investigated riders was 15.99% in southern China (Zhang et al., 2018).

Chi-square tests were conducted for age, educational level, and familiarity with traffic regulations in order to analyze the correlations among the three independent variables. As shown in Table 2a and Fig. 3, of the 6,941 total valid cases, the Fisher's exact test result showed that there is a significant correlation between age and FTR, that is, delivery riders between the ages of 25 and 30 are most familiar with traffic regulations. As shown in Table 2b and Fig. 3, there is a significant correlation between educational level and FTR: delivery riders with high school education are most familiar with traffic regulations. Overall, FTR was significantly associated with age and education, suggesting a possible deeper relationship between these variables.

Despite the advantages to this study of self-reported data, is important to account for the systematic biases in the questionnaire method of measurement (Af Wåhlberg, 2009), which include underreporting and false positives in the data (Af Wåhlberg, 2011). Af Wåhlberg et al. (2015) concluded that self-reported data is unreliable due to reporting and dissemination bias, and to common method variance, which may occur when utilizing both independent and dependent variables collected from the same source. It was necessary, therefore, to conduct a multiple collinearity test. Table 3 shows that the tolerance values of educational level, age, and FTR in relation to both crashes and helmet use were all > 0.1. In addition, the variance inflation factor (VIF) of each variable was < 10, which indicates that there was no serious collinearity among these five variables. Age, education, and FTR are thus taken as the explanatory variables of the model for further analysis.

4.2. Mediator analysis results

4.2.1. Helmet use

A hypothesis of this study is the assumption on which the mediator model is based: that some independent variables will affect the dependent variable indirectly through a mediator variable. Traditional ordered logistic regression models were established to compare their data results and model fitting indicators with those of the mediator ordered logistic models. Table 4b describes the mediator model for helmet use. Two paths are shown with different dependent variables, indicated by Y. Path 2 shows helmet use as the dependent variable, influenced directly (W) by the three independent variables. In Path 1, the dependent variable is FTR, itself influenced by the other two independent variables prior to influencing helmet use in Path 2. That is, FTR influences helmet use indirectly as a mediating variable (M). In contrast, the traditional ordered logistic regression model described in Table 4a has only one dependent variable, helmet use, and only one path, the direct influence of the three variables.

Based on various combinations of the factors considered in this study, a series of ordered logistic models were estimated with WLSMV, and evaluated to obtain the final models for helmet use and for crash occurrence. RMSEA, CFI, and WRMR were employed to effectively evaluate the goodness of fit of both the traditional and mediator ordered logistic models. Those models with the best goodness of fit were used for comparison.

The helmet use results show that even though the mediator ordered logistic model in Table 4b has complicated path variation and multiple influencing factors, its fitting index results (RMSEA $= 0.000 < 0.08$, CFI $= 1.000 > 0.9$, TLI $= 1.000 > 0.9$, WRMR $= 0.007 < 0.08$) are nearly the same as the traditional ordered logistic regression model in Table 4a, with only the slight difference in the traditional model's WRMR $= 0.009 < 0.08$.

Table 2a
Age*FTR chi-square tests.

	Value	df	Asymp. Sig. (2-sided)	Monte Carlo Sig. (2-sided)			Monte Carlo Sig. (1-sided)		
				Sig.	99% Confidence Interval		Sig.	99% Confidence Interval	
					Lower Bound	Upper Bound		Lower Bound	Upper Bound
Pearson Chi-square	46.123[a]	12	0.000	.000b	0.000	0.000			
Likelihood Ratio	46.219	12	0.000	.000b	0.000	0.000			
Fisher's Exact Test	45.771			.000b	0.000	0.000			
Linear-by-linear Association	24.540c	1	0.000	.000b	0.000	0.000	.000b	0.000	0.000
N of Valid Cases	6,941								

a. 0 cells (0.0%) had expected count<5. Minimum expected count was 14.82.
b. Based on 10,000 sampled tables with starting seed 92,208,573.
c. Standardized statistic is 4.954.

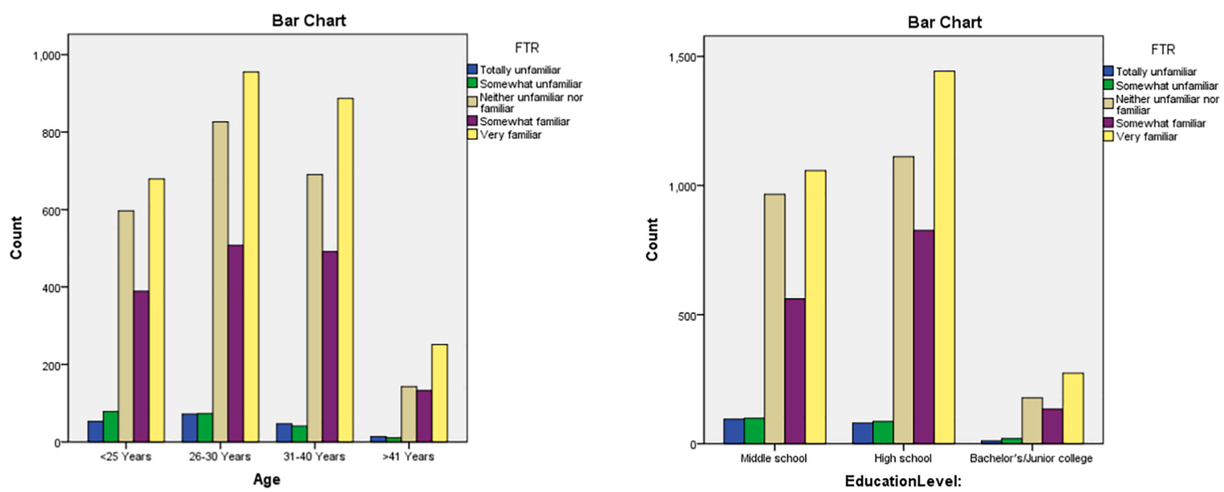

Fig. 3. Relationship of FTR to Age and Educational Level.

Table 2b
Educational Level*FTR Chi-square Tests.

	Value	df	Asymp. Sig. (2-sided)	Monte Carlo Sig. (2-sided)			Monte Carlo Sig. (1-sided)		
				Sig.	99% Confidence Interval		Sig.	99% Confidence Interval	
					Lower Bound	Upper Bound		Lower Bound	Upper Bound
Pearson Chi-square	35.207a	6	0.000	.000b	0.000	0.000			
Likelihood Ratio	35.197	6	0.000	.000b	0.000	0.000			
Fisher's Exact Test	34.933			.000b	0.000	0.000			
Linear-by-linear Association	29.321c	1	0.000	.000b	0.000	0.000	.000b	0.000	0.000
N of Valid Cases	6,941								

a. 0 cells (0.0%) had expected count<5. Minimum expected count was 16.53.
b. Based on 10,000 sampled tables with starting seed 1,993,510,611.
c. Standardized statistic is 5.415.

Table 3
Multiple collinearity test.

Variable	Tolerance	VIF
Dependent variable: Helmet Use		
1. Educational level	0.991	1.010
2. Age	0.991	1.009
3. Familiarity with traffic regulations	0.992	1.008
Dependent variable: E-bike crash occurrence		
Educational level	0.991	1.010
Age	0.991	1.009
3. Familiarity with traffic regulations	0.992	1.008

VIF: Variance inflation factor.

At least three important observations can be made in Table 4b. First, FTR mediates the effect of educational level on helmet use. As is apparent, there is a negative relationship between E^2 (bachelor's/junior college) and helmet use, but the effect between E^1 (high school) and helmet use is not significant. Yet both E^2 and E^1 have significant effects on FTR in comparison with middle school.

FTR is shown to positively influence helmet use, and also to have the greatest impact of the independent variables. Total indirect effect, under Special Mediating Effects in the table, refers to the effect that an independent variable indirectly has on the dependent variable through the mediating variable, while total effect refers to the sum of the variable's direct and indirect effects. The indirect effect of educational level on helmet use via FTR is statistically significant, though the total effect is not significant: since educational level has no direct influence on helmet use, it is only reflected by the mediating variable. FTR thus plays a

Table 4a
Ordered logistic model of helmet use.

Variable	Coefficient (γ)	S.E.	Est./S. E. (t)	P-Value
Path (Y: helmet use)				
Familiarity with traffic regulations (base: very familiar)				
Totally unfamiliar	-0.704	0.102	-6.883	0.000
Somewhat unfamiliar	-0.338	0.119	-2.830	0.005
Neither unfamiliar nor familiar	-0.347	0.051	-6.871	0.000
Somewhat familiar	-0.126	0.059	-2.149	0.032
Educational level (base: middle school)				
High school	0.036	0.045	0.793	0.428
Bachelor's/junior college	-0.141	0.072	-1.956	0.050
Age (base: <25 Years)				
26-30 Years	0.086	0.052	1.649	0.099
31-40 Years	0.203	0.056	3.647	0.000
>41 Years	0.291	0.091	3.183	0.001
Thresholds				
Helmet use$1: occasional use	-2.356	0.065	-36.143	0.000
Helmet use$2: frequent use	-1.395	0.055	-25.447	0.000
Fitting indexes				
Number of free parameters		11		
RMSEA		0.000		
CFI		1.000		
TLI		1.000		
WRMR		0.009		

Y indicates the dependent variable.

completely mediating effect between educational level and helmet use.

Second, FTR mediates the effect of age on helmet use. Table 4b shows that ages 31–40 and > 41 years) can directly affect both delivery riders' FTR and helmet use; and the direct effect of FTR on helmet use is positively significant. Although the indirect effect of age on helmet use mediated by FTR is negatively significant, the total effect of age on helmet use is statistically significant. Since age has both direct and indirect effects on helmet use, FTR plays a partial mediating effect between them.

Finally, since educational level does not have a significant direct effect on helmet use, the total effect of education, age, and FTR on helmet use is positively significant. The total indirect effect of education and age on helmet use mediated by FTR is also statistically significant.

Table 4b demonstrates that FTR plays multiple mediating roles between the effects of educational level and age on helmet use. Consequently, when compared with the results of the traditional ordered logistic regression model shown in Table 4a, it is clear that the mediator ordered logistic model can establish a deeper understanding of the relationships between variables and their influences.

4.2.2. *E-bike crash occurrence*

Table 5 compares the traditional ordered logistic regression model for e-bike crash occurrence with the mediator ordered logistic model. The results demonstrate that the mediator model has good model-fitting indexes (RMSEA = 0.000 < 0.08, CFI = 1.000 > 0.9, TLI = 1.000 > 0.9, WRMR = 0.007 < 0.08), better than the traditional model (0.009). The difference between the models for e-bike crash occurrence is even greater than the difference for helmet use (Table 4).

FTR is shown to be a mediating variable between educational level and e-bike crash occurrence. As is evident in Table 5b, crashes have no significant relationship with a high school level of education, and the effect of bachelor's/junior college is also not significant. Yet, as seen in Table 4b in relation to helmet use, both college and high school have significant positive effects on FTR in comparison with middle school.

FTR negatively influences e-bike crash occurrence, and has the largest direct impact of the independent variables. Because the indirect effect of both levels of education via FTR are negatively significant, and

Table 4b
Mediator ordered logistic model of helmet use.

Variable	Coefficient (γ)	S.E.	Est./S. E. (t)	P-Value
Paths				
1. Y: M-familiarity with traffic regulations				
Educational level (base: middle school)				
E^1-High school (a_1)	0.134	0.028	4.788	0.000
E^2-Bachelor's/junior college (b_1)	0.201	0.049	4.085	0.000
Age (base: <25 Years)				
A^1-26-30 Years (c_1)	0.036	0.034	1.070	0.285
A^2-31-40 Years (e_1)	0.131	0.035	3.695	0.000
A^2-31-40 Years (e_1)	0.256	0.054	4.744	0.000
2. Y: W-helmet use				
Familiarity with traffic regulations (d_1)	0.191	0.021	9.062	0.000
E: Educational level (base: middle school)				
E^1: High school (a_2)	0.034	0.044	0.778	0.437
E^2: Bachelor's/junior college (b_2)	-0.143	0.071	-2.028	0.043
Age (base: <25 Years)				
A^1-26-30 Years (c_2)	0.079	0.051	1.548	0.122
A^2-31-40 Years (e_2)	0.193	0.055	3.527	0.000
A^3->41 Years (f_2)	0.281	0.092	3.060	0.002
Thresholds				
FTR$1: Totally unfamiliar	-1.781	0.041	-43.362	0.000
FTR$2: Somewhat unfamiliar	-1.437	0.035	-40.573	0.000
FTR$3: Neither unfamiliar nor familiar	-0.143	0.031	-4.573	0.000
FTR$4: Somewhat familiar	0.417	0.031	13.264	0.000
Helmet use$1: occasional use	-2.127	0.059	-36.057	0.000
Helmet use$2: frequent use	-1.181	0.045	-26.156	0.000
Special mediating effects				
$E^1 \rightarrow M \rightarrow W$ (a_1*d_1)	0.026	0.006	4.238	0.000
$E^2 \rightarrow M \rightarrow W$ (b_1*d_1)	0.038	0.010	3.725	0.000
Total indirect effect of E on W ($a_1*d_1+ b_1*d_1$)	0.064	0.014	4.549	0.000
Total effect of E on W ($a_1*d_1+ b_1*d_1+a_2+b_2$)	-0.045	0.095	-0.470	0.638
$A^1 \rightarrow M \rightarrow W$($c_1*d_1$)	0.007	0.006	1.063	0.288
$A^2 \rightarrow M \rightarrow W$($e_1*d_1$)	0.025	0.007	3.426	0.001
$A^3 \rightarrow M \rightarrow W$($f_1*d_1$)	0.049	0.012	4.193	0.000
Total indirect effect of A on W ($c_1*d_1+e_1*d_1+ f_1*d_1$)	0.081	0.020	3.954	0.000
Total effect of A on W ($c_1*d_1+e_1*d_1+f_1*d_1+c_2+e_2+f_2$)	0.634	0.151	4.190	0.000
Total indirect effect of E, A on W	0.145	0.028	5.235	0.000
Total effect of E, A on W	0.589	0.176	3.352	0.001
Fitting indexes				
Number of free parameters		17		
RMSEA		0.000		
CFI		1.000		
TLI		1.000		
WRMR		0.007		

Y indicates the dependent variable; M = mediated by FTR; W = direct influence on helmet use; a_1, b_1, c_1, d_1, e_1, f_1, a_2, b_2, c_2, e_2, f_2, are coefficients of each path.

the total direct effect of education is not significant, FTR plays a completely mediating role between educational level and e-bike crash occurrence.

FTR also mediates the effect of age on crash occurrence. Table 5b demonstrates that the age of delivery riders does not directly affect traffic crashes, but the indirect effect of age via FTR is negatively significant. Thus, FTR has a completely mediating effect between age and e-bike crash occurrence.

Finally, since neither age nor educational level directly affect crashes, the total effect of educational level and age is not significant. On

Table 5a
Ordered logistic model of e-bike crash occurrence.

Variable	Coefficient (γ)	S.E.	Est./S. E. (t)	P-Value
Path (Y: helmet use)				
Familiarity with traffic regulations (base: very familiar)				
Totally unfamiliar	0.309	0.092	3.362	0.001
Somewhat unfamiliar	0.381	0.093	4.095	0.000
Neither unfamiliar nor familiar	0.232	0.040	5.849	0.000
Somewhat familiar	0.234	0.044	5.358	0.000
Educational level (base: middle school)				
High school	-0.034	0.035	-0.979	0.327
Bachelor's/junior college	-0.061	0.061	-1.001	0.317
Age (base: <25 Years)				
26-30 Years	0.053	0.043	1.240	0.215
31-40 Years	0.066	0.044	1.505	0.132
>41 Years	0.051	0.067	0.760	0.448
Thresholds				
Crash occurrence$1: 1-3 times	0.914	0.045	20.212	0.000
Crash occurrence$2: 4-6 times	2.392	0.058	41.088	0.000
Crash occurrence$3: >6 times	2.665	0.066	40.290	0.000
Fitting indexes				
Number of free parameters		12		
RMSEA		0.000		
CFI		1.000		
TLI		1.000		
WRMR		0.009		

the other hand, the total indirect effect of education and age as mediated by FTR is statistically significant.

Table 5b thus shows that FTR plays multiple completely mediating roles between the effects of educational level and age on e-bike crash occurrence. When compared with the results shown in Table 5a, it is clear, as it was with helmet use, that the mediator ordered logistic model reveals influences and relationships between variables not apparent in the traditional ordered logistic regression model.

5. Discussion

Due to the potentially complex relationships between variables, this study proposed a mediator ordered logistic model. Two mediator models were built to investigate the direct and indirect relationships between e-bike riders' educational level, age, FTR, helmet use, and crash occurrence. The models were compared with traditional logistic regression models and did, in fact, reveal deeper relationships between variables. The following discussion therefore refers to the results from the mediator models.

5.1. Helmet use

Age was found to have a significant positive effect on helmet use, which is consistent with Nordfjærn et al. (2010), but this study also found that the higher an individual's educational level, the more likely he or she was to refuse to wear a helmet. This finding agrees with results from a prior empirical study by Tseng (2013), and also makes sense in light of Ajzen's theory of planned behavior (TPB, 1991). That is, a higher educational level might affect e-cyclists' attitudes toward behavioral norms and their perceived degree of control over their behavior.

Educational level and age also predicted helmet use indirectly by influencing couriers' familiarity with traffic regulations (FTR). FTR itself had the greatest positive direct effect on helmet use, which is reflective of similar findings in previous studies (Lawson et al., 2013; Wang et al., 2012; Yang et al., 2018). While survey results showed that only 40% of delivery riders were "totally unfamiliar" with traffic regulations, almost all owned helmets, and>90% reported "frequently" wearing them, a proportion far better than the 17.2% of e-bike riders in general (Wang et al., 2012). This difference is likely a consequence of the delivery industry requiring helmets, and perhaps convincing riders of the helmet's importance to their safety. That delivery riders reported a relatively low level of education could also help explain why, as a group, they are more likely than other e-bike riders to wear helmets.

5.2. E-bike crash occurrence

This study's results showed that educational level had no significant direct effect on crashes. While this is inconsistent with previous studies of e-cyclists in general (Useche et al., 2019), the sample in the current study were delivery riders only. Most couriers, of any educational level, have received some safety training either before starting their jobs or through their delivery companies once working. However, the mediating effect analysis showed that education did have an indirect negative effect on crash occurrence. FTR thus played a completely mediating role in the effect of educational level on e-bike crash occurrence.

This study have also found that the total combined direct and indirect effects of each of the variables is greater than the direct effects that other studies, and FTR had a completely mediating effect in the influence of age. Age did not directly affect crash occurrence, which is consistent with a previous study (An et al., 2013). However, older delivery riders in this study reported a strong FTR, which, as mentioned, is consistent with Nordfjærn et al. (2010), while the FTR of younger riders was weak. Consequently, although age did not affect crashes directly, younger drivers' lower awareness made them more indirectly prone to traffic crashes. Conversely, because older and better educated delivery riders had a stronger awareness of traffic regulations, they were likely to be involved in fewer crashes.

6. Conclusion

The increased use of e-bikes in many cities has been accompanied by an increase in their crash involvement, many of which have a high level of severity. Finding appropriate countermeasures has become urgent. It has been established that wearing helmets reduces the severity of crashes, and as there has been little research specifically on e-bikes, this study examined some of the factors affecting helmet use as well as e-bike crashes. Because a sizeable portion of regular e-bike users in Shanghai are couriers, these delivery riders were chosen as the subjects for this study.

This paper conducted a systematic study of e-bike safety by surveying 6,941 delivery riders in Shanghai, applying mediator ordered logistic regression analysis to uncover relationships among some of the potentially influencing human factors. Two mediator models were built to explore the relationships between educational level, age, familiarity with traffic regulations (FTR), helmet use, and e-bike traffic crashes. While both age and education had direct effects on helmet use, FTR's effect was greatest, and it additionally played a mediating role between both educational level and age and helmet use. Improving younger riders' FTR may be the most effective way to increase helmet use. Traffic safety education courses could be created for e-cyclists, and passing such courses could be made mandatory for obtaining a license. Also, because discomfort was the main reason subjects gave for not wearing helmets, manufacturers and governing agencies could cooperate to improve helmet design.

In contrast to their effects on helmet use, neither age nor educational level had direct effects on e-bike crash occurrence. In these cases, FTR played a completely mediating role. As it was the only connection in this study between education, age, and crashes, familiarity with traffic regulations was demonstrated to be extremely beneficial to e-bike safety. The delivery industry could take the lead in developing safety education courses and campaigns to reduce the crash risk of their current and

Table 5b
Mediator ordered logistic model of e-bike crash occurrence.

Variable	Coefficient(γ)	S.E.	Est./S. E. (t)	P-Value
Paths				
Y: Z- E-bike crash occurrence				
Familiarity with traffic regulations (d_1)	-0.121	0.017	-6.930	0.000
E: Educational level (base: middle school)				
E^1: High school (a_2)	-0.028	0.035	-0.806	0.420
E^2: Bachelor's/junior college (b_2)	-0.052	0.060	-0.863	0.388
Age (base: <25 Years)				
A^1-26-30 Years (c_2)	0.052	0.042	1.214	0.225
A^2-31-40 Years (e_2)	0.069	0.043	1.580	0.114
A^3->41 Years (f_2)	0.055	0.067	0.825	0.409
Thresholds				
FTR$1: Totally unfamiliar	-1.781	0.041	-43.362	0.000
FTR$2: Somewhat unfamiliar	-1.437	0.035	-40.573	0.000
FTR$3: Neither unfamiliar nor familiar	-0.143	0.031	-4.573	0.000
FTR$4: Somewhat familiar	0.417	0.031	13.264	0.000
Crash occurrence$1: 1-3 times	0.747	0.038	19.747	0.000
Crash occurrence$2: 4-6 times	2.217	0.054	41.348	0.000
Crash occurrence$3: >6 times	2.491	0.063	39.821	0.000
Special mediating effects				
$E^1 \rightarrow M \rightarrow Z$ ($a_1{*}d_1$)	-0.016	0.004	-3.935	0.000
$E^2 \rightarrow M \rightarrow Z$ ($b_1{*}d_1$)	-0.024	0.007	-3.521	0.000
Total indirect effect of E on Z ($a_1{*}d_1 + b_1{*}d_1$)	-0.040	0.010	-4.188	0.000
Total effect of E on Z ($a_1{*}d_1 + b_1{*}d_1 + a_2 + b_2$)	-0.120	0.079	-1.526	0.127
12604755861050175704566 26225 $A^1 \rightarrow M \rightarrow Z(c_1{*}d_1)$	-0.004	0.004	-1.057	0.290
12604755861050175704566 26225 $A^2 \rightarrow M \rightarrow Z(e_1{*}d_1)$	-0.016	0.005	-3.261	0.001
12604755861050175704566 26225 $A^3 \rightarrow M \rightarrow Z(f_1{*}d_1)$	-0.031	0.008	-3.900	0.000
Total indirect effect of A on Z ($c_1{*}d_1 + e_1{*}d_1 + f_1{*}d_1$)	-0.051	0.014	-3.704	0.000
Total effect of A on Z ($c_1{*}d_1 + e_1{*}d_1 + f_1{*}d_1 + c_2 + e_2 + f_2$)	0.124	0.120	1.033	0.301
Total indirect effect of E, A on Z	-0.091	0.019	-4.701	0.000
Total effect of E, A on Z	0.005	0.144	0.032	0.975
Fitting indexes				
Number of free parameters		17		
RMSEA		0.000		
CFI		1.000		
TLI		1.000		
WRMR		0.007		

M = mediated by FTR; Z = direct influence on e-bike crashes; $a_1, b_1, c_1, d_1, e_1, f_1, a_2, b_2, c_2, e_2, f_2$ are coefficients of each path.

potential delivery riders. At the workplace, the industry could also involve the older couriers, who exhibited higher levels of FTR, in mentoring the younger through regular one-on-one peer safety awareness education. Although the results of this study reflect only the safety of delivery riders in China, improving riders' FTR may increase helmet use and decrease crash occurrence more broadly. With further research, governmental authorities in many cities with heavy e-bike use may be able to apply our findings to develop e-bike safety countermeasures such as appropriate legislation and training.

In addition to its practical application, this study makes an important theoretical contribution by its examination of the intermediary relationships of the factors influencing helmet use and e-bike crash occurrence. Compared with the traditional logistic regression model, the mediator ordered logistic model was demonstrated as superior for modeling these interrelated human factors; specifically, the mediator models were successful in capturing crucial influential factors that were not apparent in the traditional models. Accordingly, this study opens the door to further study to expand and supplement the literature by positioning familiarity with traffic regulations as an important variable that may mediate in the relationships between other potentially influencing factors.

The main limitation of this study is that all data were collected by surveying delivery riders. First, although the delivery industry is a major user of e-bikes and is in a position to take safety measures that can be an important precedent, the sample may not be representative of the general population. Second, as discussed in Section 3, bias is unavoidable in self-reported data, and FTR, helmet use, and crash occurrence might be particularly subject to bias. Since, however, a practical goal of this study is improving safety education, using riders' self-reported behaviors may be an advantage, as they are more likely to be receptive to changing those behaviors they already see as problems. Nonetheless, further research using real crash data is recommended to confirm this study's results, with the caveat that helmet use was not considered as a variable influencing crashes. Self-reported helmet use can also be compared with observed use to understand the variable from both subjective and objective aspects.

It should also be noted that because a primary focus of this study was mediation analysis, the authors chose to limit the tested variables in order to limit the complexity of possible indirect paths of influence. The authors anticipate that future e-bike research in other areas will enhance the inferences made in this study. Studies could be conducted that consider risk exposure, such as daily delivery trips made, distance traveled, or the ratio of annual average daily traffic (AADT) to crash count. Other modelling approaches such as Structural Equation Modeling (SEMs) can be tested, as well as other variables and targeted areas of study such as alcohol consumption and organizations' safety cultures. This study's use of mediation analysis should have many applications in traffic safety.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Author Contribution.

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