Mathematical Biosciences and Engineering

MBE, 20(5): 9135–9158.
DOI: 10.3934/mbe.2023401
Received: 12 January 2023
Revised: 12 February 2023
Accepted: 26 February 2023
Published: 14 March 2023

http://www.aimspress.com/journal/MBE

Research article

Determinants of switching behavior to wear helmets when riding e-bikes, a two-step SEM-ANFIS approach

Peng Jing*, Weichao Wang, Chengxi Jiang, Ye Zha and Baixu Ming

School of Automotive and Traffic Engineering, Jiangsu University, Zhenjiang, China

* **Correspondence:** Email: jingpeng@ujs.edu.cn.

Abstract: E-bikes have become one of China's most popular travel modes. The authorities have issued helmet-wearing regulations to increase wearing rates to protect e-bike riders' safety, but the effect is unsatisfactory. To reveal the factors influencing the helmet-wearing behavior of e-bike riders, this study constructed a theoretical Push-Pull-Mooring (PPM) model to analyze the factor's relationship from the perspective of travel behavior switching. A two-step SEM-ANFIS method is proposed to test relationships, rank importance and analyze the combined effect of psychological variables. The Partial Least Squares Structural Equation Model (PLS-SEM) was used to obtain the significant influencing factors. The Adaptive Network-based Fuzzy Inference System (ANFIS), a nonlinear approach, was applied to analyze the importance of the significant influencing factors and draw refined conclusions and suggestions from the analysis of the combined effects. The PPM model we constructed has a good model fit and high model predictive validity (GOF = 0.381, $R^2 = 0.442$). We found that three significant factors tested by PLS-SEM, perceived legal norms ($\beta = 0.234$, $p < 0.001$), perceived inconvenience ($\beta = -0.117$, $p < 0.001$) and conformity tendency ($\beta = 0.241$, $p < 0.05$), are the most important factors in the effects of push, mooring and pull. The results also demonstrated that legal norm is the most important factor but has less effect on people with low perceived vulnerability, and low subjective norms will make people with high conformity tendency to follow the crowd blindly. This study could contribute to developing refined interventions to improve the helmet-wearing rate effectively.

Keywords: helmet-wearing behavior; switching intention; Push-Pull-Mooring model; perceived legal norm; PLS-SEM; ANFIS; nonlinear

1. Introduction

E-bikes, electric-powered two-wheeled vehicles, have received considerable attention during the past decade due to environmental protection, labor-saving and low-cost advantages. In China, E-bikes have become one of the most popular travel modes [1], and the total number of e-bikes had been close to 300 million in 2021 [2]. However, accidents related to e-bikes took up a large proportion of all traffic accidents. For example, more than 50% of the total road traffic accidents were related to e-bike accidents in two Chinese provinces (Jiangsu and Zhejiang) in 2019 [3]. In accidents for e-bike riders, head injury is the leading cause of injury and death [4,5]. Previous research revealed that wearing helmets can effectively ensure the head safety of e-bike riders and reduce 51% of head injury risk [6]. A high helmet-wearing rate seems crucial to protect travel safety for e-bike riders [7].

The helmet-wearing rate is the aggregate reflection of e-bike riders' individual wearing behavior. The literature related to riders' intention and behavior for helmet use focuses on bicycles and motorcycles, which contributes to scientific helmet promotion plans for policymakers to improve helmet-wearing rates and protect riders' travel safety [8]. In China, e-bikes have high social recognition, and ownership continues to increase [9]. E-bikes have a different risk of accident fatalities than motorcycles and bicycles [10]. In addition, existing studies have found a discrepancy in riding violations between different riding modes. For instance, the results from zhou et al. [11] showed that e-bike riders are more likely to break the law than bicycle riders, and Truong et al. [12] found that motorcycle riders were more than twice as likely to use mobile phones while riding as e-bike riders. Riding without wearing a helmet belongs to violating traffic laws, especially in countries like China that have enacted helmet regulations. Different travel modes may lead to a discrepancy in helmet use behavior and influencing factors for riders [13]. Therefore, the current research results on bicycles and motorcycles' helmet-wearing behaviors may not be applicable in China for e-bikes. To our knowledge, only zhou et al. [14] analyzed helmet-wearing behavior from the perspective of objective variables, such as weather, travel time and travel purpose after the Chinese helmet regulation was enacted. Apart from that, Wang et al. [15] focused on the delivery riders' e-bike helmet use with the survey data in 2019, but the helmet regulation had not yet begun to spread at that time and the delivery riders' wearing behavior may not behave the same as regular riders for occupational safety. In general, there is a lot of research work on the wearing behavior of e-bike helmets to explore.

The Traffic Administration Bureau of China launched a nationwide safety campaign named "One Helmet, One Belt" on April 21, 2020, to increase helmet-wearing [16]. Currently, 31 Chinese provinces have issued more than 70 local regulations (as shown in Figure 1) to require residents to wear helmets when riding e-bikes. The legislation imposes mandatory constraints on people's behavior and is an effective way for the government to regulate public behavior [17], but the legislation might not be sufficient. For example, the helmet-wearing rate reached 93.39% after Qingyuan, one city in Guangdong Province, issued a helmet-wearing rule in November 2020 but quickly dropped to 56.40% after only three months [18]. The refined interventions are essential to cooperate with the enforcement activities of helmet regulations [19], which needs to identify influencing factors and explore further relationships between factors and helmet-wearing intention, such as nonlinear relationships [20]. Compared with linear models, such as linear regression and the Structural Equation Model（SEM）in existing studies for helmet-wearing behavior [14,21,22], the Adaptive Network-based Fuzzy Inference System (ANFIS) is a very powerful approach to dealing with the complex, nonlinear relationship between input and output factors [23] and rank the factors' importance [24]. At present, helmet regulations are being promoted nationwide in China, and the intention of switching from not wearing to wearing helmets when riding e-bikes involves hundreds of millions of people's daily travel safety. However, less research has focused on helmet-wearing behavior and the switching intention of e-bike riders in China. To fill in the gaps and formulate refined interventions to effectively improve the wearing rate of helmets, we proposed the following research questions (RQs) and tried to solve them.

RQ1: What factors can significantly influence the intention of switching to helmet-wearing?

RQ2: Among the influencing factors, which factors are more important?

RQ3: Under the combined effect of different important factors, will the intention of e-bike riders to wear helmets change?

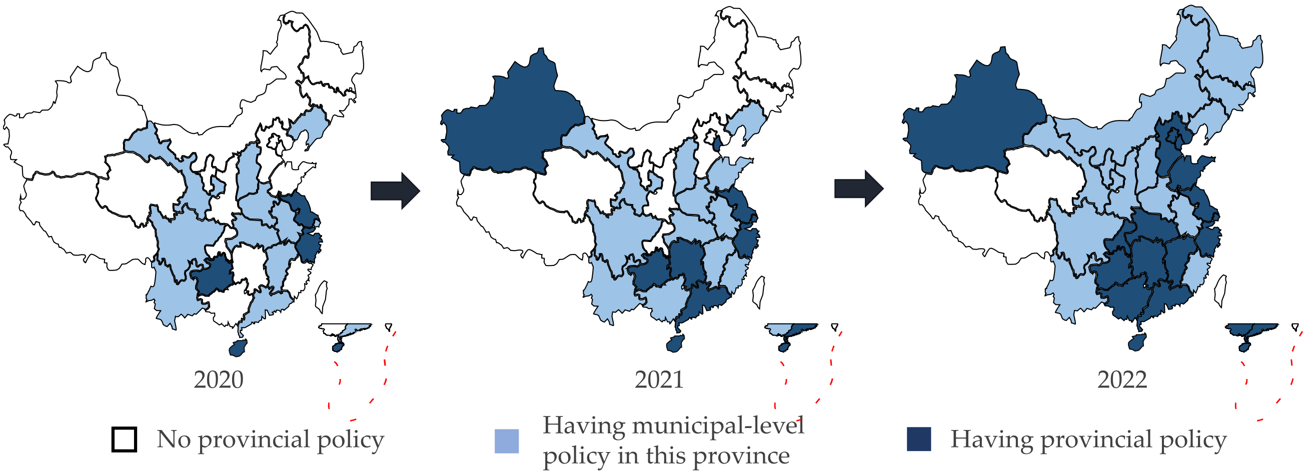

Figure 1. Helmet regulation promotion process from 2020 to 2022 in China.

This study aims to clarify the factors affecting helmet-wearing switching intention and analyze the factor's importance and relationship to provide targeted suggestions for helmet policy promotion. According to the research questions and purpose, we set three objectives: 1) Identifying the factors that affect the switching intention of helmet-wearing; 2) Ranking the factors' importance; 3) Providing targeted suggestions to improve helmet-wearing rates. This research introduces the Push-Pull-Mooring (PPM) framework into the field of helmet-wearing behavior for the first time and constructs a theoretical model of the helmet-wearing switching intention of e-bikes. The Partial Least Square Structural Equation Model (PLS-SEM) and the ANFIS were combined to reveal the possible linear and nonlinear relationship between the influencing factors and the dependent variable. A two-step SEM-ANFIS method was constructed to rank the importance of psychological variables while verifying the significance of path relationships. We obtained a more refined path relationship by analyzing the changes in helmet-wearing switching intention under the combined effect of different important factors. Overall, the PPM model we constructed is a theoretical framework for the e-bike riders' helmet-wearing behavior, and the two-step SEM-ANFIS method results could provide targeted suggestions for improving helmet-wearing rates.

The remainder is organized as follows: the next section provides a brief review of the literature on the construction of the PPM model and hypothesis. Section 3 describes the method of data collection, measurement structure and two-step SEM-ANFIS applied for the analysis. Section 4 presents the results of both PLS-SEM and ANFIS analysis. The theoretical and practical implications, limitations and further directions are given in Section 5. The final Section 6 consists of the conclusion of this research.

2. Literature review and theoretical model

The PPM model originated in the field of human migration [25] and has been widely applied to explain switching behavior in many fields, such as environmental protection, healthcare services and online applications [26–28]. Based on the Theory of Planned Behavior (TPB) and Protection Motivation Theory (PMT), this study constructs a PPM model for helmet-wearing switching behavior of e-bikes by expanding the characteristic variables, such as perceived legal norms, habits and conformity tendency. The PPM model was deemed useful for understanding switching behavior because of its powerful explanation. We analyzed the influencing factors and path relationships of helmet-wearing switching intention from three perspectives: push, mooring and pull. The switching intention (SI) was defined as the behavior intention to switch from not wearing to wearing a helmet. The PPM model for helmet-wearing switching intention and hypotheses were constructed in Figure 2.

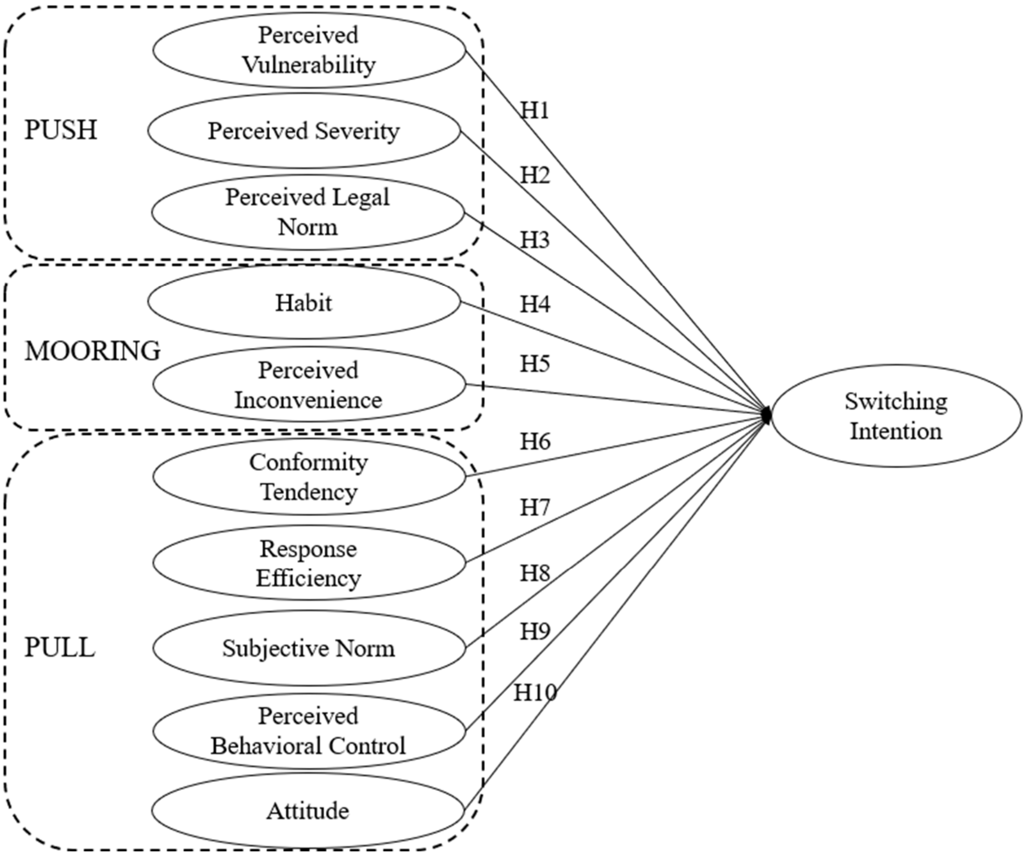

Figure 2. The PPM model and research hypotheses.

2.1. Push effects

In the PPM model, the push effect refers to the positive factor that motivates people to leave the original place [29]. This study uses the perceived vulnerability and perceived severity in the PMT, and extended perceptual legal normative factors as the push factors, analyzing the positive impact of the disadvantages of not wearing a helmet on the switching intention.

Perceived vulnerability (PVU) refers to an e-bike rider's estimate of the likelihood of injury in a traffic accident. Perceived severity (PSE) refers to the severity of injury without a helmet. Generally, the perceived risk of injury and perceived injury severity directly affect an individual's safe behavior [30]. Due to concerns about accidents and serious injuries, e-bike riders may wear helmets to protect their heads. Therefore, we incorporated PVU and PSE into the push effects to examine their switching intention of helmet use.

Perceived legal norm (PLN) is the level at which road users perceive legal consequences for violating traffic rules [31]. Paschall et al. [32] found that legal norms correlated significantly with young people's intention to drink. Traffic police's punishment for non-helmeted cyclists may prompt them to switch to wearing helmets, so we expand PLN as one of the push factors.

Based on the analysis of PVU, PSE and PLN on the helmet-wearing intention of e-bike riders, we propose the following three hypotheses:

H1: Perceived Vulnerability has a positive impact on switching intention;

H2: Perceived Severity has a positive impact on switching intention;

H3: Perceived Legal Norm has a positive impact on switching intention.

2.2. Mooring effects

Mooring effects contain negative factors that may hinder the switching intention [25]. This study applied habit (HAB) and perceived inconvenience (PI) as mooring factors in the PPM model. We analyzed the negative impact of the inconvenience caused by the helmet and the long-term habit of not wearing behavior on helmet-wearing switching intention.

Habit is an unintentional response that occurs when an individual engages in an activity over a long period [33]. Lai et al. [28] incorporated Habit into the PPM model and found that habit negatively impacts the switching intention of middle-aged and elderly patients to adopt cloud medical services. In this study, the habit was defined as the habit of riding an e-bike without a helmet.

Perceived inconvenience is defined as the extent to which an individual feels inconvenient and uncomfortable [30]. Barbarossa and Pelsmacker [34] used structural equation models to reveal that consumer perceived inconvenience is a negative and significant factor in green purchase intention. This research defined Perceived Inconvenience as the degree of inconvenience the riders feel caused by helmet-wearing and involved perceived inconvenience as a negative factor to explain e-bike riders' switching intention.

Based on the above application and results on habit and perceived inconvenience in behavior switching research, we propose the following hypotheses:

H4: Habit negatively influences switching intention;

H5: Perceived Inconvenience negatively influences switching intention.

2.3. Pull effects

The pull effects are positive factors facilitating migrants to their destination [25]. Five psychological variables, namely conformity tendency (CT), response efficiency (RE), attitude (ATT), subjective norm (SN) and perceived behavior control (PBC), were included in the pull effects. We analyzed five psychological variables' pull effect on switching intention.

Conformity stands for the tendency to follow others' behavior [35]. Zhou et al. [36] found that conformity tendency is a significant factor influencing pedestrians' intention to cross the street. In addition, e-bike riders with a higher conformity tendency are more likely to violate traffic rules [37]. Whether or not other e-bike riders wear a helmet could impact the individual intention and behavior, so we apply conformity tendency as one of the pull factors influencing the switching intention.

Response efficiency refers to the perceived effectiveness of risk-protective behaviors and is a sub-constituent of the coping evaluation in PMT [38]. The study by Chamroonsawasdi et al. [39] found that response efficiency significantly and positively affected dietary activity to prevent diabetes. Since wearing a helmet protects the e-bike rider's head safety and reduces the chance of injury, we defined response efficiency as the perceived protective effectiveness of helmets when riding an e-bike and included it in the pull effects.

Subjective norm (SN), perceived behavior control (PBC) and Attitude (ATT) are all factors from the TPB, which is currently one of the most widely used models in behavioral research [40]. Previous research demonstrates that SN, PBC and ATT in TPB positively affect human intention [40]. In this study, subjective norm refers to the influence of relatives and friends on the individual's helmet-wearing switching intention, perceived behavior control refers to the individual's ability to wear a helmet, and attitude is defined as a positive attitude towards wearing a helmet.

The above five psychological variables were included in the pull effects to analyze their influence on helmet-wearing switching intention, and the following hypotheses were proposed:

H6: Conformity tendency positively impacts switching intention;

H7: Response efficiency positively impacts switching intention;

H8: Subjective norm positively impacts switching intention;

H9: Perceived behavior control positively impacts switching intention;

H10: Attitude positively impacts switching intention.

3. Methods

According to the constructed theoretical PPM model, we designed the variable measurement scale and questionnaire. After obtaining the data through the survey, the mathematical analysis method and the two-step SEM-ANFIS approach were used to test the model and obtain the output value to rank the factors' importance. Moreover, we analyzed the nonlinear relationship and combined effects. The analysis process is shown in Figure 3.

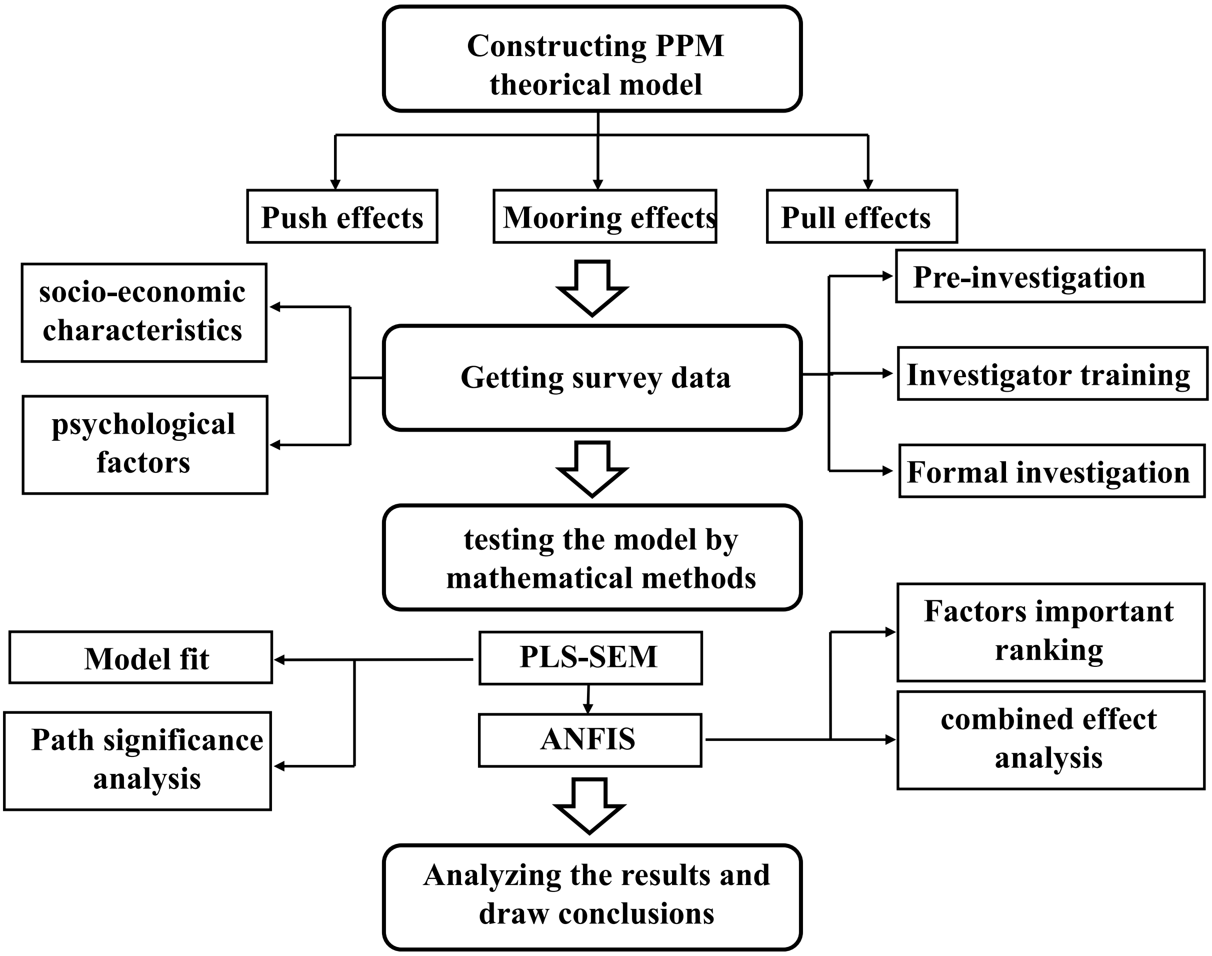

Figure 3. The flow chart for analysis process.

3.1. Measurement

This study designed a survey using a questionnaire to investigate helmet-wearing for e-bike riders. The questionnaire includes three sections. The first section introduces the research purpose and investigation background. The respondents' socio-economic characteristics and trip attributes were counted in the second section. The final section focuses on the impact of psychological factors on respondents' helmet-wearing intention. We adopted measurement items for eleven constructs from previously validated research, and these items were answered according to a seven-point Likert scale ranging from one strongly disagree to seven strongly agree. Table 1 shows the eleven constructs with items and their source.

Table 1. Questionnaire items in this research.

Constructs	Items	Sources
Perceived Vulnerability (PVU)	PVU1: Wearing a helmet can reduce the risk of head injuries in e-bike accidents. PVU2: Wearing a helmet can protect me when I ride an e-bike. PVU3: Wearing a helmet can reduce the impact on the head in an e-bike accident.	Brijs et al., 2014 [41]
Perceived Severity (PSE)	PSE1: Riding an e-bike without a helmet could lead to severe cerebral hemorrhage and even a threat to my life. PSE2: My head could be hurt in a traffic accident, and I would have to pay a lot of medical bills due to not wearing a helmet. PSE3: Riding an e-bike without a helmet could lead to disability due to head nerve damage if a traffic accident happens. PSE4: Riding an e-bike without a helmet could result in death from severe head injuries if a traffic accident happens.	Fallah Zavareh et al., 2018 [5]
Perceived Legal Norm (PLN)	PLN1: If a police officer finds me riding an e-bike without a helmet, I will be fined after the e-bike helmet-wearing legislation is enacted. PLN2: If a police officer finds me riding an e-bike without a helmet, I will be taught after legislation on e-bike helmet-wearing is issued. PLN3: If a police officer finds me riding an e-bike without a helmet, I will be stopped from leaving after legislation on e-bike helmet wearing is issued.	Tang et al., 2021 [37]
Conformity Tendency (CT)	CT1: When I find that other e-bike rider wearing helmets, I will do the same. CT2: When I realized that most e-bike riders wear helmets, I will do the same. CT3: I am always willing to take traffic safety advice (helmets, etc.).	Tang et al., 2021 [37]
Response Efficacy (RE)	RE1: I find it difficult to wear a helmet every time I ride an e-bike. RE2: I know how to adjust the straps of most bicycle helmets to fit my head. RE3: I could easily get a helmet if I want. RE4: I can wear a helmet on my e-bike if I want.	Shafiei and Maleksaeidi, 2020 [41]
Attitude (ATT)	ATT1: Riding an e-bike with a helmet is beneficial to me. ATT2: Riding an e-bike with a helmet is a good decision. ATT3: I think it is wise to wear a helmet when riding an e-bike. ATT4: I think it is a good idea to wear a helmet when riding an e-bike.	Roberts et al., 2006 [42]
Subjective Norm (SN)	SN1: My relatives support me to wear a helmet when riding an e-bike.	Borhan et al., 2019

Continued on next page

Constructs	Items	Sources
	SN2: My colleagues/classmates agree that I wear a helmet when riding an e-bike.	[43]
	SN3: My friends want me to wear a helmet when I ride my e-bike.	
Perceived Behavioral Control (PBC)	PBC1: It is difficult to wear a helmet every time I ride an e-bike.	Ross, 2011 [44] Brijs et al., 2014 [22]
	PBC2: I know how to adjust the straps of most bicycle helmets so that they fit my head correctly.	
	PBC3: I can wear a helmet on my e-bike if I want to.	
Habit (HAB)	HAB1: I often forget my helmet when I ride an e-bike.	Ross, 2011 [44] Brijs et al., 2014 [22]
	HAB2: I feel like I have a habit of riding my e-bike without a helmet.	
	HAB3: I would still be riding an e-bike without a helmet if there was no policy to encourage me to wear a helmet.	
Perceived Inconvenience (PI)	PI1: If I wear a helmet while riding an e-bike, my vision will be blocked and it will be inconvenient for me to ride.	Olsen et al., 2007 [45] Nguyen et al., 2016 [46]
	PI2: If I wear a helmet while riding an e-bike, my hearing will be affected and it will be inconvenient for me to ride.	
	PI3: Riding an e-bike with a helmet makes me feel uncomfortable.	
	PI4: Wearing a helmet outside requires me to spend extra time and energy on the storage of the helmet.	
	PI5: Wearing a helmet outside requires me to spend extra time and energy on the anti-theft problem of the helmet.	
Switching Intention (SI)	SI1: I plan to wear a helmet while riding an e-bike after Jiangsu province implemented the mandatory helmet-wearing regulation.	Wang et al. 2020 [30]
	SI2: I plan to wear a helmet when riding an e-bike after the mandatory helmet-wearing regulation is implemented in Jiangsu province.	
	SI3: I want to wear a helmet when riding an e-bike after the mandatory helmet-wearing regulation is implemented in Jiangsu province.	

3.2. Data collection and sample

We conducted a pre-survey online and collected 112 questionnaires, and the formal questionnaire was modified and improved according to the pre-survey results. The formal survey period is from June 24 to June 25, 2021, and was carried out by investigators in shopping malls and other public places in Zhenjiang, Jiangsu. A total of 48 investigators were involved in the survey, and they were trained to select respondents randomly to ensure sampling randomness. We collected 387 questionnaires with the interviewee informed and excluded questionnaires with filling logical errors or choosing all the same options. Furthermore, we removed the respondents who wore helmets before the promulgation of the law because we aimed to switch intentions. Finally, 322 valid questionnaires constituted our final sample with an effective rate of 83.2%.

Table 2. Descriptive statistics of participant characteristics.

Demographic variables		Frequency	Percentages
Gender	Male	164	50.93%
	Female	158	49.07%
Age	≤ 19	29	9.01%
	20–30	72	22.36%
	30–39	141	43.79%
	≥ 40	80	24.84%
Marriage	Yes	157	48.76%
	No	165	51.24%
Education	Primary school or below	7	2.17%
	Junior middle school	50	15.53%
	Senior high school	74	22.98%
	Junior college	70	21.74%
	College degree	110	34.16%
	Master's degree or above	11	3.42%
Income (RMB)	< 2000 (less than 313$)	85	26.40%
	2000–3999 (313$–626$)	53	16.46%
	4000–6000 (626$–940$)	88	27.33%
	> 6000 (above 940$)	96	29.81%
Job	Enterprise manager	40	12.42%
	Professionals	25	7.77%
	Service workers	112	34.79%
	Clerks	23	7.14%
	Students	55	17.08%
	Others	67	20.8%
E-bike travel frequency (one week)	< 3	192	59.63%
	4–6	82	25.46%
	7	48	14.91%
E-bike helmet frequency (one week)	< 3	217	67.41%
	4–6	46	14.28%
	7	59	18.31%
Punishment experience for not wearing helmets	Stopped and fined by traffic police	64	19.88%
	Witnesses or hear others being Stopped without helmets by traffic police	108	33.54%
	No such experience	150	46.58%

Table 2 shows the demographic distribution and travel characteristics of the respondents. The males were 50.93%, and the females were 49.07%, which was almost equal. The average age of the respondents was 33.7 years. The most occupation is service workers (34.79%), and more than 70% of respondents earned less than 6000 yuan per month. Although the samples in this study are younger and have low-level income compared to the statistics of Chinese people [47], they fit with the crowd characteristics of e-bike riders [48]. A total of 40.37% had ridden e-bikes for more than four days per week and 14.91% every day. However, most of the respondents (67.41%) wore helmets less than three times per week after enacted legislation. We investigated the Participants' experiences of being punished for not wearing a helmet and found that 19.88% were stopped and fined by police. Therefore, our sample could be considered representative of Chinese e-bike riders.

3.3. SEM-ANFIS

Structural equation modeling (SEM) has been widely used to assess human behavior and examines the relationships among latent variables as a linear method [49]. Literature suggests two methods of SEM. First, Covariance-based SEM (CB-SEM) determines the relationships based on minimizing the difference between theoretical and estimated covariance matrices [50]. Second, Partial Least Squares-SEM (PLS-SEM) estimates the relationships by maximizing the explained variance of the endogenous variables [51]. Considering that PLS-SEM is better suited for examining exploratory models [52], requires no assumptions of homogeneity and normality in the data, and deals with small sample sizes, unlike CB-SEM [53], we use PLS-SEM to test the relationship in the PPM model.

The PLS-SEM approach is usually explained by the measurement model and the structural model. The measurement model exhibits the relationship of observed variables with their respective constructs, and the structural model exhibits the interrelationships between the constructs by determining the path coefficients. The measurement model is expressed by flowing reflective measurement (Eq (1)) and formative measurement (Eq (2)) [54]:

$$x_i = \pi_{i0} + \pi_i \xi + \varepsilon_i \tag{1}$$

$$\xi = \sum_i w_i x_i + \delta \tag{2}$$

where, x_i is observed variable; π_i is the loading corresponding to the observed variable; ξ is the latent variable related to observed variables; ε_i is the error term; w_i is the weight corresponding to observed variables; δ is the residual term.

The structural model is expressed as follows:

$$\xi_j = \beta_{j0} + \sum_i \beta_{ji} \xi_i + v_j \tag{3}$$

where ξ_j is jth latent variable with ith of latent variables; β is the latent variables' regression coefficient term; v_j is an error term related to ξ_j.

Jang proposed an adaptive network based fuzzy inference system (ANFIS), also known as the adaptive neural fuzzy reasoning system, in 1993 [55]. ANFIS is a new type of fuzzy reasoning system structure that organically combines fuzzy logic and neuronal network, which is a multi-layer feedforward network using a hybrid algorithm of backpropagation algorithm and least squares method to adjust the premise parameters and conclusion parameters, and finally generates If-Then rules [55]. ANFIS model has been applied in empirical behavioral research to predict and reveal the influencing factors and their importance to the willingness to accept autonomous vehicles and the successful development of hotels [20,24]. Considering that the relationship between variables might be possibly nonlinear and the SEM focuses on the linear relationship mainly, we use the ANFIS to overcome the drawback.

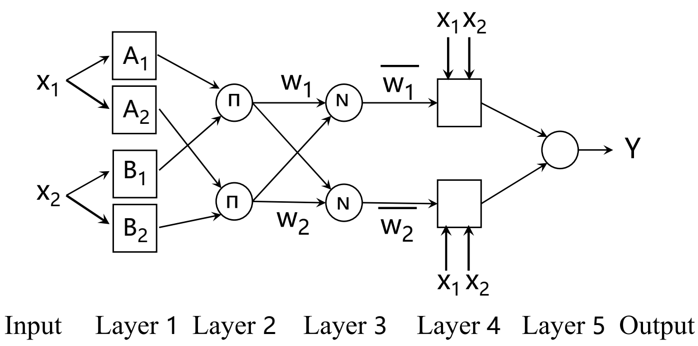

Figure 4. ANFIS typical structural model.

For simplicity, a singleton Sugeno fuzzy model with two inputs, "x1" and "x2", and one output Y has the following If-Then rules:

Rule1：If "x_1" is "A_1" and "x_2" is "B_1" then "$z_1 = p_1 x_1 + q1\ x_2 + r_1$"

Rule2：If "x_1" is "A_2" and "x_2" is "B_2" then "$z_2 = p_2 x_1 + q_2 x_2 + r_2$"

where "x_1" and "x_2" are non-fuzzy inputs, A_i (or B_i) are fuzzy sets, z_i is the output value; p_i, q_i and r_i are parameters of the output function.

The typical ANFIS model structure is shown in Figure 4, and each of the five layers for the ANFIS model is described below [56].

Layer 1: layer 1 is an adaptive unit with a function defined by:

$$O_{1,i} = \mu_{A_i}(x_1)\text{ , for } i = 1, 2, 3 \tag{4}$$

$$O_{1,i} = \mu_{B_{i-3}}(x_2)\text{ , for } i = 4, 5, 6 \tag{5}$$

where x and y are inputs, $O_{1,i}$ represents the output of node i in layer l, and A_i and B_{i-3} are membership functions for inputs.

Layer 2: Every node in layer 2 is a fixed node labeled Π, which multiplies the incoming inputs from layer 1 (Eq (2)):

$$O_{2,i} = w_i = \mu_{A_i}(x_1) * \mu_{B_i}(x_2)\text{ , for } i = 1, 2 \tag{6}$$

Each node output in this layer is called the firing strength of a rule, which means the weight degree of the if-then rules.

Layer 3: Every node in this layer is a fixed node labeled N. The ratio of the ith rules' firing strength is calculated in the ith node as a sum of all rules' firing strengths and normalizes the firing strengths from layer 2.

$$O_{3,i} = \overline{w_i} = \frac{w_i}{w_1 + w_2}\text{ , for } i = 1, 2 \tag{7}$$

Layer 4: The nodes in this layer are adaptive nodes comprising a linear combination of functions.

$$O_{4,i} = \overline{w_i} \cdot f_i \tag{8}$$

where $\overline{w_i}$ is a normalized firing strength output from layer 3, and f_i is the consequent parameter.

Layer 5: The single node in this layer is a fixed node labeled and overall output, summing the output of layer 4.

$$O_{4,i} = \sum_i \overline{w_i} \cdot f_i = \frac{\sum_i w_i \cdot f_i}{\sum_i w_i} \tag{9}$$

Based on the PPM theoretical model and path hypothesis, a mathematical analysis method of two-stag SEM-ANFIS was constructed to analyze the linear and nonlinear relationship in factors and dependents by using PLS-SEM and ANFIS. We used PLS-SEM to test and obtain significant factors affecting switching intention and included these significant factors in the ANFIS model for prediction as input variables. According to the importance ranking of the factors from the predicted value of ANFIS, we obtained a more refined path relationship by analyzing the changes in switching intention under the combined influence of different important factors in the three types of factors of push, mooring and pull.

4. Results

4.1. Data quality assessment

Data quality is a prerequisite for constructing models, including reliability tests and validity tests. Reliability was decided by Cronbach's Alpha and composite reliability (CR). The formula for Cronbach's alpha is:

$$\text{Cronbach's } \alpha = \frac{n}{\sigma_x^2 \cdot (n-1)} \left(\sigma_x^2 - \sum \sigma_i^2\right) \tag{10}$$

where the σ_x^2 is the total test score variance, n is the number of variables' items, and σ_i^2 is the item variance.

The CR value reflects whether all items in each variable could explain the variable consistently, and the formula stands for the total amount of true score variance relative to the total score variance [57]:

$$CR = \frac{(\sum \lambda_i)^2}{[(\sum \lambda_i^2) + \sum \theta]} \tag{11}$$

where λ_i is the ith indicator's standardized loading, and θ is of indicator's error item.

As shown in Table 3, both Cronbach's Alpha and CR are higher than the standard values of 0.7 and 0.6. Scale validity is determined by convergence validity and discriminant validity. Convergence validity is based on two conditions: item loading (λ) must exceed 0.7 [58], and the average variance extracted (AVE) for each construct must exceed 0.5 to indicate good convergence validity [59]. As shown in Table 4, the square root value of AVE for each variable is greater than the correlation value with other variables, indicating good discriminant validity [59]. The results of the data quality assessment showed that the data had good reliability and validity. The AVE is computed using the following formula:

$$AVE = \frac{\sum {\lambda_i}^2}{[(\sum \lambda_i^2) + \sum \theta]} \tag{12}$$

where λ_i is the ith indicator's standardized loading, and θ is of indicator's error item.

Table 3. Reliability and convergent validity test of the constructs.

Potential variable	Item	Factor Loadings (λ)	Cronbach's Alpha	AVE	CR
Perceived vulnerability (PVU)	PVU1	0.912	0.9061	0.9406	0.8408
	PVU2	0.930			
	PVU3	0.909			
Perceived severity (PSE)	PSE1	0.926	0.9308	0.9507	0.8282
	PSE2	0.904			
	PSE3	0.932			
	PSE4	0.875			
Perceived legal norm (PLN)	PLN1	0.851	0.8815	0.9259	0.8068
	PLN2	0.940			
	PLN3	0.902			
Conformity tendency (CT)	CT1	0.910	0.9037	0.9397	0.8386
	CT2	0.940			
	CT3	0.896			
Response efficacy (RE)	RE1	0.845	0.9155	0.9404	0.798
	RE2	0.895			
	RE3	0.916			
	RE4	0.913			
Attitude (ATT)	ATT1	0.887	0.9291	0.9495	0.8246
	ATT2	0.909			
	ATT3	0.920			
	ATT4	0.915			
Subjective norm (SN)	SN1	0.886	0.8743	0.9225	0.7988
	SN2	0.900			
	SN3	0.895			
Perceived behavioral control (PBC)	PBC1	0.762	0.8129	0.8903	0.7312
	PBC2	0.890			
	PBC3	0.905			
Habit (HAB)	HAB1	0.965	0.8915	0.9238	0.802
	HAB2	0.855			
	HAB3	0.863			
Perceived inconvenience (PI)	PI1	0.909	0.898	0.8901	0.6276
	PI2	0.970			
	PI3	0.610			
	PI4	0.615			
	PI5	0.581			
Switching intention (SI)	SI1	0.937	0.9284	0.9545	0.875
	SI2	0.956			
	SI3	0.913			

Table 4. Discrimination validity.

	ATT	CT	HAB	PBC	PI	PLN	PSE	PSU	RE	SI
T	0.9081									
CT	0.5273	0.9157								
HAB	0.0051	0.1495	0.8956							
PBC	0.217	0.228	0.1034	0.8551						
PI	0.0126	0.0153	0.1888	0.1348	0.7922					
PLN	0.2126	0.1827	0.0513	0.2741	0.01	0.8982				
PSE	0.6162	0.6248	0.0795	0.1151	0.0024	0.1723	0.9101			
PSU	0.525	0.4431	0.0586	0.31	0.0682	0.3493	0.5205	0.917		
RE	0.5713	0.4125	0.0605	0.3455	0.1577	0.1983	0.4731	0.5827	0.8933	
SI	0.3786	0.3776	0.038	0.1625	0.0944	0.3799	0.2353	0.4005	0.2717	0.9354

Note: Square root of AVE in bold on diagonals.

4.2. PLS-SEM results

4.2.1. Structural model quality

The PLS-SEM model was built using the SmartPLS Software (Version 3.0), The model R^2 and goodness of fit (GoF) were selected as the evaluation indicators of model quality, and the results are shown in Table 5. R^2 reflects the explanatory strength of the model, and the evaluation criteria are 0.19 (low), 0.33 (moderate) and 0.67 (high) [58]. The results show that the model constructed in this institute has a reasonable explanatory strength, reaching 44.2%. GoF is used to test the validity of model prediction, the evaluation criteria are 0.1 (low), 0.25 (moderate) and 0.36 (high) [55], and the model test results show that the GoF value is 0.381, which has a high model prediction effectiveness. Overall, the PPM model constructed by this institute is of good quality. The GoF is computed using the following formula:

$$Gof = \sqrt{\overline{AVE} \cdot \overline{R^2}} \tag{13}$$

where the AVE is calculated by Eq (12), R^2 is the model R^2.

Table 5. The test of structural model quality.

Indicators	Criterion	Results	Evaluation
R^2	0.19 (low), 0.33 (moderate), 0.67 (high)	0.442	Reasonable
GoF	0.10 (low), 0.25 (moderate), 0.36 (high)	0.381	Good

4.2.2. Hypothesis testing results

Figure 5 shows the hypothesis testing results of the PPM model. The results showed that perceived legal norm ($\beta = 0.234$, $p < 0.001$), perceived severity ($\beta = 0.23$, $p < 0.01$), perceived vulnerability ($\beta = 0.192$, $p < 0.01$), conformity tendency ($\beta = 0.241$, $p < 0.05$), subjective norm ($\beta = 0.15$, $p < 0.05$) and attitude ($\beta = 0.198$, $p < 0.05$) had a positive and significant impact on switching intention, and perceived inconvenience (β = -0.117, $p < 0.001$) and habit (β = -0.113, $p < 0.001$) had a significantly negative impact on switching intention, while response efficiency (β = 0.01, $p > 0.05$) and perceptual behavior control (β = 0.059, $p > 0.05$) had no significant impact on switching intention. See Table 6 for details.

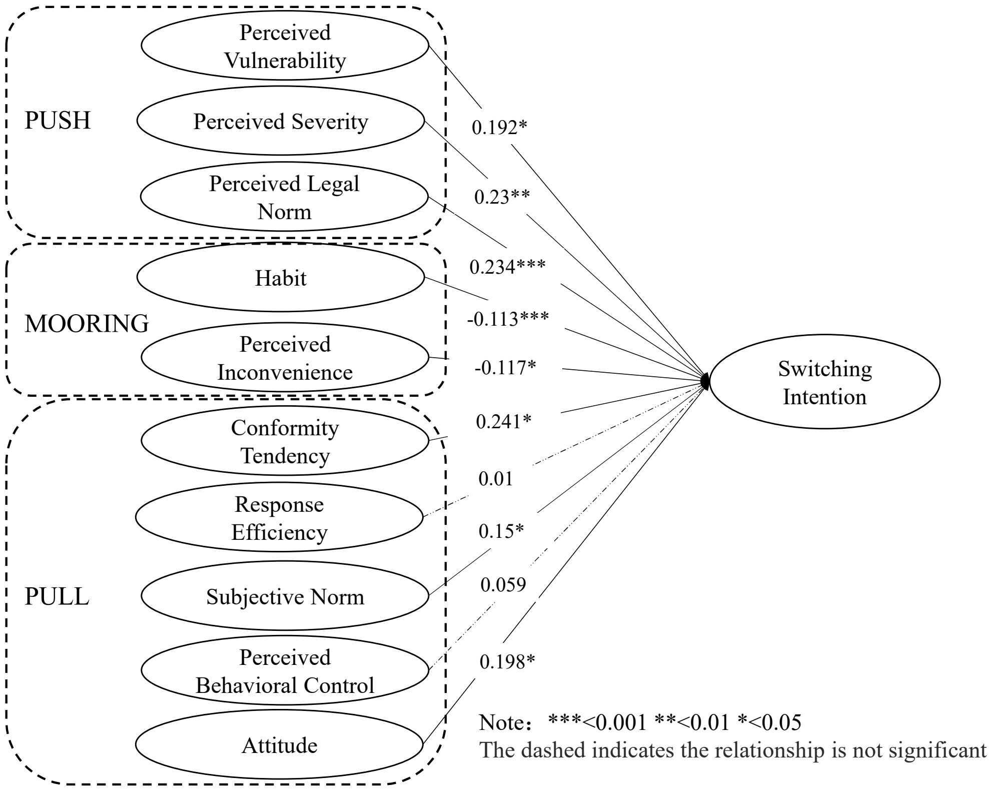

Figure 5. Results of hypotheses testing for the PPM model.

Table 6. Results of hypotheses testing.

Hypothesis	Path	Path coefficients	p-value	Support
H1	PVU→SI	0.192	0.01	Yes
H2	PSE→SI	0.236	0.004	Yes
H3	PLN→SI	0.234	0.000	Yes
H4	HAB→SI	-0.113	0.000	Yes
H5	PI→SI	-0.117	0.017	Yes
H6	CT→SI	0.241	0.044	Yes
H7	RE→SI	0.01	0.877	No
H8	SN→SI	0.15	0.040	Yes
H9	PBC→SI	0.059	0.319	No
H10	ATT→SI	0.198	0.016	Yes

4.3. ANFIS results

The ANFIS model in this research was conducted in MATLAB Version R2018b with the Neuro-Fuzzy Designer toolbox (The MathWorks, Natick, MA, USA). Eight variables significantly impact switching intention in the PLS-SEM model test results were extracted as input variables for ANFIS. The total samples were divided into a training set (50%, 161 samples), a checking set (20%, 65 samples) and a testing set (30%, 96 samples). Gaussian membership functions (Gaussian MFs) were used to convert the 7-level Likert scale into three fuzzy levels of low, medium and high, and set the training number was 200 epochs. We obtained the predicted values, and the Root Mean Square Error (RMSE) between the observed and predicted values is 0.7321, within an acceptable range.

4.3.1. Importance ranking

By analyzing the nonlinear relationship between the input variable and the predicted value of switching intention, the importance of each variable is obtained according to the change of the switching intention brought by the input variables (as shown in Figure 6). We found that the perceived legal norm, perceived inconvenience and conformity tendency are the most important factors in push, mooring and pull effects.

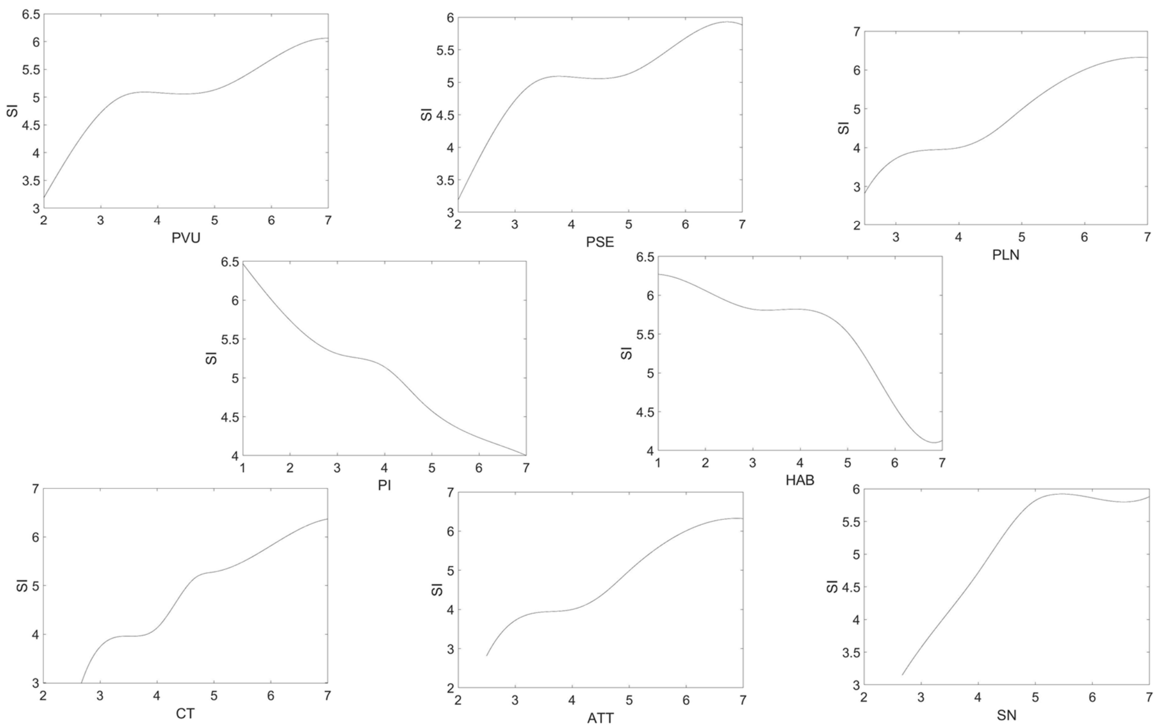

Figure 6. The importance of input variables to the switching intention.

4.3.2. Combined effect

Furthermore, we analyzed the changes in switching intention under the combined effect of two factors in the push, mooring and pull effects in order to more accurately analyze the influence relationship of various types of factors on switching intention (as shown in Figure 7).

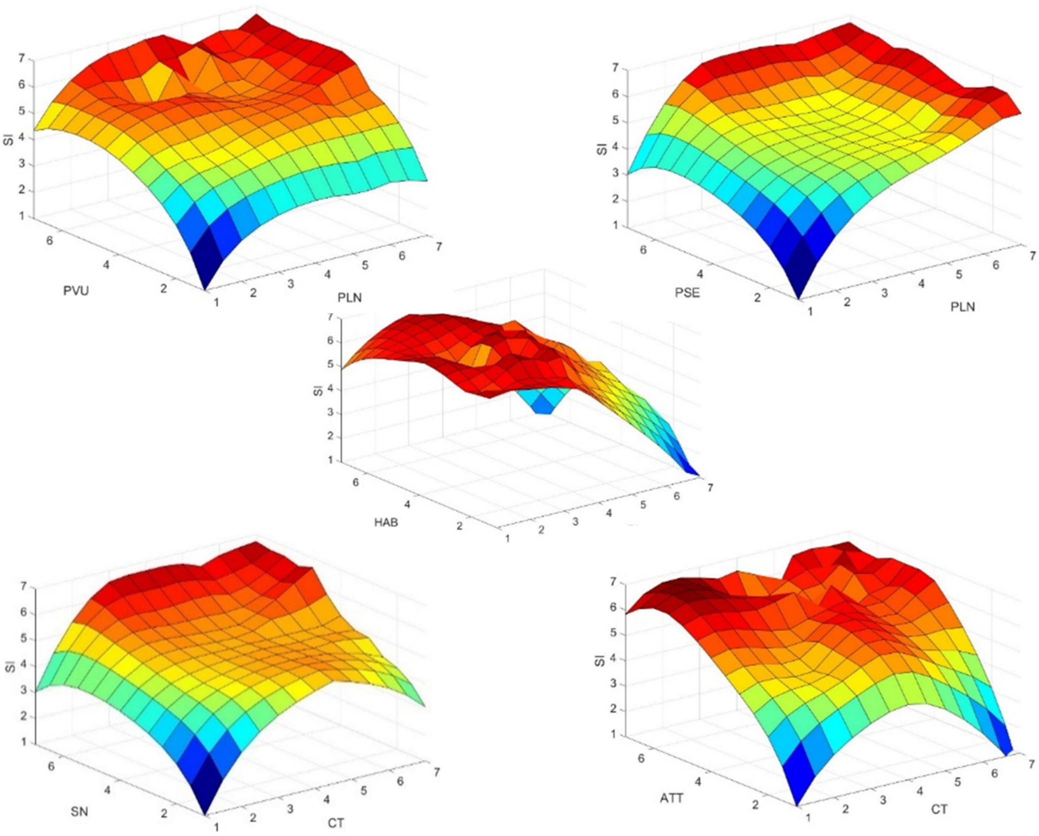

Figure 7. The combined effect on the switching intention.

5. Discussion

5.1. Theoretical implications

This research attempts to use the PPM model to explain e-bike riders' switching intention from the push, mooring and pull aspects. The model fitness test states that the conceptual model has strong explementary power on e-bike riders' switching intention on wearing helmets. The results indicate the adaptability of this proposed PPM model, therefore the researchers could use this theoretical framework to analyze the helmet-wearing behavior with different research purposes or other travel behavior switching. Furthermore, the ANFIS results show that the most important influencing factors in the three effects of push, mooring and pull are the perceived legal norm, the perceived inconvenience and the conformity tendency. We analyzed the change of switching intention under the combination of the most important factors and residual factors in each effect to explore the relationship between influencing factors and helmet-wearing switching intention in a deeper way. The two-step SEM-ANFIS approach provides an analysis framework to find the significant factors, rank their importance and explore the combined effects. Meanwhile, the analysis framework above is a theoretical guidance to help the practitioners implement work. First, constructing the theoretical model and involving possible influencing factors. Second, testing the significance by SEM and choosing the significant factors for inputs. Third, inputting the significant factors into ANFIS and obtaining the predicted output. Finally, analyzing the nonlinear relationship and combined effects, and drawing a conclusion.

5.2. Practical implications

5.2.1. Push factors

We found that perceived legal norm was significantly correlated with the switching intention. This conclusion is consistent with [60], which assertion that traffic accident legislation could make drivers actively or consciously avoid traffic violations. Inversely, this result is different from [61], who reached the opposite conclusion. Two main reasons may contribute to mixed views of perceived legal norm between this study and the others. First, Jiangsu province early started implementing regulations on e-bikes, issuing 50 RMB penalties (equal to around 7 $) for no-wearing helmet behavior. Most Chinese e-bike riders belong to economically disadvantaged subpopulations [37]. They might value 50 RMB more than others. Second, local traffic authorities have carried out activities and increased police force to investigate and punish this behavior after the “One Helmet One Belt” event. E-bike riders feel the increase of police on the road and are likely to wear helmets

The most important influencing factor in the push factors was the perceived legal norm. Figure 7 shows that under the influence of lower perceived vulnerability, with the rise of perceptual legal norms, the improvement of switching intention is not obvious, indicating that people with low perceived vulnerability have limited deterrence of legislation. The main reason might be that they do not think an accident will happen to ride an e-bike for fluke mentality. Therefore, policymakers should pay more attention to publicizing the possibility of a traffic accident to e-bike riders, such as providing the annual number and the e-bike-related accident rate.

5.2.2. Mooring factors

The influence of two factors on the switching intention is both negative in the mooring factors. The significant result on perceived inconvenience is consistent with [34], and the ANFIS results showed that perceived inconvenience is more important than habit as a hindrance factor. The combined effect results of these two factors further prove that people with lower perceived inconvenience and weaker habits of not wearing helmets have a higher intention to wear helmets. Therefore, helmet manufacturers should focus on the portability of e-bike helmets. Besides, anti-theft and storage are also important factors, so e-bike manufacturers should add storage and anti-theft systems to helmets.

5.2.3. Pull factors

Conformity tendency statistically impacts e-bike riders’ switching intention positively, which is consistent with previous studies exploring pedestrians’ violating crossing behavior [61]. Based on the combined effect results, we found that conformity tendency has a significant two-sidedness. Under low subjective norms and attitudes, with the rise of conformity tendency, the switching intention shows a trend of first rising and then declining. The main reason might be that the individual’s conformity will lead to a vacillating behavior intention. The switching intention rises when the conformity tendency rises from a low to a medium level. When the conformity tendency rises from a medium level to a high level, the population with low subjective norms and attitudes is easily affected by riders who do not wear helmets, so their own helmet-wearing intention declines. Low attitudes and subjective norms will lead to blind conformable intention not to wear a helmet.

5.3. Limitations and future direction

This research provided exciting findings while also having several limitations. First, since the switching behavior is rather complex, many other factors, such as satisfaction and moral norms, might also influence helmet-wearing behavior. Second, the road travel environment, weather, helmet type and travel time might influence the helmet-wearing behavior intention. Hence, future research could extend these factors and explore the influence from the combined effects of subjective and objective factors. Third, the data was only collected with a structured interview in one city. Data collected from more samples, more channels and cities with different legislation situations could be considered to improve the persuasion of the results, especially for the ANFIS model. Furthermore, the punishment from traffic police, the direct effect of helmet regulations, is not involved in this research. The participants could be divided into different groups by multi-group analysis based on their experience of punishment to analyze the heterogeneity and identify the effects of law enforcement.

6. Conclusions

We constructed a PPM model and used the two-step SEM-ANFIS method to analyze the questionnaire survey data, verify the path significance of push, mooring and pull variables that affect the helmet-wearing switching intention for e-bike riders in China. After ranking the importance of variables and analyzing the changes in switching intention under the interaction of different types of factors, the following conclusions are obtained:

The most important variables in push, mooring and pull are the perceived legal norm, perceived inconvenience and conformity tendency. On the basis of maintaining law enforcement actions, helmet storage facilities and devices could be installed in parking places or e-bikes so as to improve e-bike riders' willingness to wear helmets, further influence more riders to wear helmets, and form a good travel atmosphere for wearing helmets.

Under the low perceived vulnerability, the increase in switching intention brought by the rise of the perceived legal norm is not obvious, indicating that for people with low perceived vulnerability, the impact of traffic police' deterrence will be reduced under the fluke mentality. Awareness of the vulnerability of accidents for e-bike riders is needed to ensure the effectiveness of helmet legislation.

For people with low attitudes and subjective norms, it is easy to blindly follow the crowd and ride without wearing helmets. It is necessary to improve the attitude and personal safety awareness through media publicity, safety lectures, etc., so as to avoid e-bike riders' blind conformism and follow the trend without wearing helmets, and improve the helmet-wearing rate.

Acknowledgments

This work was supported by the National Natural Science Foundation of China (grant number 71871107).

Conflict of interest

The authors declare there is no conflict of interest.

References

1. J. A. Zhu, S. Dai, X. Y. Zhu, Characteristics of Electric Bike Accidents and Safety Enhancement Strategies, *Urban Transp. China*, **2018** (2018), 15–20.
2. CNBN, Electric Bicycles Are Nearly 300 Million in China, Available from: http://news.cnr.cn/rebang/20211011/t20211011_525629773.shtml.
3. D. Zhang, T. F. Ren, M. M. Zhang, Y. C. Zheng, H. Y Zhou, Analysis and prevention of the causes of electric bicycle accidents based on safety checklists (in Chinese), *Sci. Technol. Innovation*, **07** (2021), 37–39. https://doi.org/10.15913/j.cnki.kjycx.2021.07.011
4. H. Leijdesdorff, J. van Dijck, P. Krijnen, C. Vleggeert-Lankamp, I. Schipper, Injury pattern, hospital triage, and mortality of 1250 patients with severe traumatic brain injury caused by road traffic accidents, *J. Neurotrauma*, **31** (2014), 459–465. https://doi.org/10.1089/neu.2013.3111
5. M. F. Zavareh, A. M. Hezaveh, T. Nordfjærn, Intention to use bicycle helmet as explained by the Health Belief Model, comparative optimism and risk perception in an Iranian sample, *Transp. Res. Part F Psychol. Behav.*, **54** (2018), 248–263. https://doi.org/10.1016/j.trf.2018.02.003
6. J. Olivier, P. Creighton, Bicycle injuries and helmet use: a systematic review and meta-analysis, *Int. J. Epidemiol*., **46** (2017), 278–292. https://doi.org/10.1093/ije/dyw153
7. Y. N. Song, W. W. Ma, J. Shen, J. G. Shen, Analysis of the relationship between helmet wearing and casualty among electric vehicle drivers (in Chinese), *Urban Rural Enterp. Health China*, **35** (2020), 7–9. https://doi.org/10.16286/j.1003-5052.2020.12.003
8. J. Kumphong, T. Satiennam, W. Satiennam, The determinants of motorcyclists helmet use: urban arterial road in Khon Kaen City, Thailand, *J. Saf. Res.*, **67** (2018), 93–97. https://doi.org/10.1016/j.jsr.2018.09.011
9. N. Xu, N. Gao, J. H. Su, Y. Yan, D. D. Zhou, J. J. Peng, Investigation on knowledge, attitude and behavior of electric bicycle drivers and riders wearing safety helmets based on wechat public account (in Chinese), *Shanghai J. Preventative Med.*, **30** (2018), 744–749. https://doi.org/10.19428/j.cnki.sjpm.2018.18803
10. C. X. Ma, D. Yang, J. B. Zhou, Z. X. Feng, Q. Yuan, Risk riding behaviors of urban e-bikes: a literature review, *Int. J. Environ. Res. Public Health*, **16** (2019), 2308. https://doi.org/10.3390/ijerph16132308
11. J. B. Zhou, Y. Y. Guo, Y. Wu, S. Dong, Assessing factors related to e-bike crash and e-bike license Plate Use, *J. Transp. Syst. Eng. Inf. Technol.*, **17** (2017), 229–234.
12. L. T. Truong, H. T. T. Nguyen, C. De Gruyter, Mobile phone use among motorcyclists and electric bike riders: a case study of Hanoi, Vietnam, *Accid. Anal. Prev.*, **91** (2016), 208–215. https://doi.org/10.1016/j.aap.2016.03.007
13. N. Haworth, A. K. Debnath, How similar are two-unit bicycle and motorcycle crashes, *Accid. Anal. Prev.*, **58** (2013), 15–25. https://doi.org/10.1016/j.aap.2013.04.014
14. J. Zhou, T. Zheng, S. Dong, X. Mao, C. Ma, Impact of helmet-wearing policy on e-bike safety riding behavior: a bivariate ordered probit analysis in Ningbo, China, *Int. J. Environ. Res. Public Health*, **19** (2022), 2830. https://doi.org/10.3390/ijerph19052830
15. X. S. Wang, J. Chen, M. Quddus, W. Zhou, M. Shen, Influence of familiarity with traffic regulations on delivery riders' e-bike crashes and helmet use: two mediator ordered logit models, *Accid. Anal. Prev.*, **159** (2021), 106277. https://doi.org/10.1016/j.aap.2021.106277

16. The Ministry of Public Security of the People's Republic of China, The Traffic Management Bureau of the Ministry of Public Security has deployed a "One Helmet, One Belt" security operation, 2020, Available from: http://www.gov.cn/xinwen/2020-04/21/content_5504613.htm.
17. M. Karkhaneh, Effectiveness of bicycle helmet legislation to increase helmet use: a systematic review, *Inj. Prev.*, **12** (2006), 76–82. https://doi.org/10.1136/ip.2005.010942
18. Guangzhou Public Security Bureau, In January, these cities in Guangdong had the lowest helmet wearing rate, 2021, Available from: https://baijiahao.baidu.com/s?id=1691405130964298455&wfr=spider&for=pc
19. T. Tang, H. Wang, B. Guo, Study on helmet wearing intention of electric bicycle riders (in Chinese), *J. Transp. Eng. Inf.*, **20** (2022), 1–17. https://doi.org/10.19961/j.cnki.1672-4747.2021.11.024
20. B. Foroughi, P. V. Nhan, M. Iranmanesh, M. Ghobakhloo, M. Nilashi, E. Yadegaridehkordi, Determinants of intention to use autonomous vehicles: findings from PLS-SEM and ANFIS, *J. Retailing Consum. Serv.*, **70** (2023), 103158. https://doi.org/10.1016/j.jretconser.2022.103158
21. Q. F. Li, O. Adetunji, C. V. Pham, N. T. Tran, E. Chan, A. M. Bachani, Helmet use among motorcycle riders in ho chi minh city, vietnam: results of a five-year repeated cross-sectional study, *Accid. Anal. Prev.*, **144** (2020), 105642. https://doi.org/10.1016/j.aap.2020.105642
22. K. Brijs, T. Brijs, S. Sann, T. A. Trinh, G. Wets, R. A. C. Ruiter, Psychological determinants of motorcycle helmet use among young adults in Cambodia, *Transp. Res. Part F Traffic Psychol. Behav.*, **26** (2014), 273–290. https://doi.org/10.1016/j.trf.2014.08.002
23. Y. C. Ho, C. T. Tsai, Comparing ANFIS and SEM in linear and nonlinear forecasting of new product development performance, *Expert Syst. Appl.*, **38** (2011), 6498–6507. https://doi.org/10.1016/j.eswa.2010.11.095
24. E. Yadegaridehkordi, M. Nilashi, M. H. N. B. M. Nasir, O. Ibrahim, Predicting determinants of hotel success and development using structural equation modelling (SEM)-ANFIS method, *Tourism Manage.*, **66** (2018), 364–386. https://doi.org/10.1016/j.tourman.2017.11.012
25. B. Moon, Paradigms in migration research: exploring 'moorings' as a schema, *Prog. Hum. Geogr.*, **19** (1995), 504–524. https://doi.org/10.1177/030913259501900404
26. J. K. Hsieh, Y. C. Hsieh, H. C. Chiu, Y. C. Feng, Post-adoption switching behavior for online service substitutes: a perspective of the push–pull–mooring framework, *Comput. Hum. Behav.*, **28** (2012), 1912–1920. https://doi.org/10.1016/j.chb.2012.05.010
27. Y. Sun, D. Liu, S. J. Chen, X. R. Wu, X. L. Shen, X. Zhang, Understanding users' switching behavior of mobile instant messaging applications: an empirical study from the perspective of push-pull-mooring framework, *Comput. Hum. Behav.*, **75** (2017), 727–738. https://doi.org/10.1016/j.chb.2017.06.014
28. J. Y. Lai, J. Wang, Switching attitudes of taiwanese middle-aged and elderly patients toward cloud healthcare services: an exploratory study, *Technol. Forecasting Social Change*, **92** (2015), 155–167. https://doi.org/10.1016/j.techfore.2014.06.004
29. H. S. Bansal, S. Taylor, Y. St. James, "Migrating" to new service providers: toward a unifying framework of consumers' switching behaviors, *J. Acad. Mark. Sci.*, **33** (2005), 96–115. https://doi.org/10.1177/0092070304267928
30. S. Wang, J. Wang, F. Yang, From willingness to action: do push-pull-mooring factors matter for shifting to green transportation, *Transp. Res. Part D Transp. Environ.*, **79** (2020), 102242. https://doi.org/10.1016/j.trd.2020.102242

31. H. Kim, The role of legal and moral norms to regulate the behavior of texting while driving, *Transp. Res. Part F Traffic Psychol. Behav.*, **52** (2018), 21–31. https://doi.org/10.1016/j.trf.2017.11.004
32. M. J. Paschall, J. W. Grube, S. Thomas, C. Cannon, R. Treffers, Relationships between local enforcement, alcohol availability, drinking norms, and adolescent alcohol use in 50 california cities, *J. Stud. Alcohol Drugs*, **73** (2012), 657–665. https://doi.org/10.15288/jsad.2012.73.657
33. M. Limayem, S. G. Hirt, W. W. Chin, Intention does not always matter: the contingent role of habit on it usage behavior, in *the 9th European Conference on Information Systems*, **13** (2001).
34. C. Barbarossa, P. De Pelsmacker, Positive and negative antecedents of purchasing eco-friendly products: a comparison between green and non-green consumers, *J. Bus. Ethics*, **134** (2016), 229–247. https://doi.org/10.1007/s10551-014-2425-z
35. A. Mehrabian, C. A. Stefl, Basic temperament components of loneliness, shyness, and conformity, *Social Behav. Pers. Int. J.*, **23** (1995), 253–263. https://doi.org/10.2224/sbp.1995.23.3.253
36. R. Zhou, W. J. Horrey, Predicting adolescent pedestrians' behavioral intentions to follow the masses in risky crossing situations, *Transp. Res. Part F Traffic Psychol. Behav.*, **13** (2010), 153–163. https://doi.org/10.1016/j.trf.2009.12.001
37. T. P. Tang, Y. T. Guo, X. Z. Zhou, S. Labi, S. L. Zhu, Understanding electric bike riders' intention to violate traffic rules and accident proneness in China, *Travel Behav. Soc.*, **23** (2021), 25–38. https://doi.org/10.1016/j.tbs.2020.10.010
38. P. Janmaimool, Application of protection motivation theory to investigate sustainable waste management behaviors, *Sustainability*, **9** (2017), 1079. https://doi.org/10.3390/su9071079
39. K. Chamroonsawasdi, S. Chottanapund, R. A. Pamungkas, P. Tunyasitthisundhorn, B. Sornpaisarn, O. Numpaisan, Protection motivation theory to predict intention of healthy eating and sufficient physical activity to prevent Diabetes Mellitus in Thai population: A path analysis, *Diabetes Metab. Syndr. Clin. Res. Rev.*, **15** (2021), 121–127. https://doi.org/10.1016/j.dsx.2020.12.017
40. L. Ajzen, From intentions to actions: a theory of planned behavior, in *Action Control*, Springer, (1985), 11–39. https://doi.org/10.1007/978-3-642-69746-3_2
41. A. Shafiei, H. Maleksaeidi, Pro-environmental behavior of university students: application of protection motivation theory, *Glob. Ecol. Conserv.*, **22** (2020), e00908. https://doi.org/10.1016/j.gecco.2020.e00908
42. R. Meade, W. Barnard, Conformity and anticonformity among Americans and Chinese, *J. Social Psychol.*, **89** (1973), 15–24. https://doi.org/10.1080/00224545.1973.9922563
43. M. N. Borhan, A. N. H. Ibrahim, M. A. A. Miskeen, Extending the theory of planned behaviour to predict the intention to take the new high-speed rail for intercity travel in Libya: Assessment of the influence of novelty seeking, trust and external influence, *Transp. Res. Part A Policy Pract.*, **130** (2019), 373–384. https://doi.org/10.1016/j.tra.2019.09.058
44. L. Ross, T. Ross, S. Farber, C. Davidson, M. Trevino, A. Hawkins, The theory of planned behavior and helmet use among college students, *Am. J. Health Behav.*, **35** (2011), 581–590. https://doi.org/10.5993/AJHB.35.5.7
45. S. O. Olsen, J. Scholderer, K. Brunsø, W. Verbeke, Exploring the relationship between convenience and fish consumption: A cross-cultural study, *Appetite*, **49** (2007), 84–91. https://doi.org/10.1016/j.appet.2006.12.002

46. T. N. Nguyen, A. Lobo, S. Greenland, Pro-environmental purchase behaviour: the role of consumers' biospheric values, *J. Retailing Consum. Serv.*, **33** (2016), 98–108. https://doi.org/10.1016/j.jretconser.2016.08.010
47. National Bureau of Statistics, China Statistical Yearbook (2022). Available from: http://www.stats.gov.cn/tjsj./ndsj/.
48. SUHO.COM, Characteristics of electric bicycle traffic accidents and safety improvement measures, (2019). Available from: https://www.sohu.com/a/289681314_782444.
49. J. Mandhani, J. K. Nayak, M. Parida, Interrelationships among service quality factors of Metro Rail Transit System: An integrated Bayesian networks and PLS-SEM approach, *Transp. Res. Part A Policy Pract.*, **140** (2020), 320–336. https://doi.org/10.1016/j.tra.2020.08.014
50. T. F. Golob, Structural equation modeling for travel behavior research, *Transp. Res. Part B Methodol.*, **37** (2003), 1–25. https://doi.org/10.1016/S0191-2615(01)00046-7
51. J. Henseler, G. Hubona, P. A. Ray, Using PLS path modeling in new technology research: updated guidelines, *Ind. Manage. Data Syst.*, **116** (2016), 2–20. https://doi.org/10.1108/IMDS-09-2015-0382
52. A. Leguina, A primer on partial least squares structural equation modeling (PLS-SEM), *Int. J. Res. Method Educ.*, **38** (2015), 220–221. https://doi.org/10.1080/1743727X.2015.1005806
53. J. F. Hair Jr, M. Sarstedt, L. Hopkins, V. Kuppelwieser, Partial least squares structural equation modeling (PLS-SEM): An emerging tool in business research, *Eur. Bus. Rev.*, **26** (2014), 106–121. https://doi.org/10.1108/EBR-10-2013-0128
54. M. Tenenhaus, V. E. Vinzi, Y. M. Chatelin, C. Lauro, PLS path modeling, *Comput. Stat. Data Anal.*, **48** (2005), 159–205. https://doi.org/10.1016/j.csda.2004.03.005
55. J. R. Jang, ANFIS: adaptive-network-based fuzzy inference system, *IEEE Trans. Syst. Man Cybern.*, **23** (1993), 665–685.
56. D. Nauck, F. Klawonn, R. Kruse, *Foundation of Neuro-fuzzy Systems*, Wiley, 1997.
57. S. Zhang, P. Jing, D. Yuan, C. Yang, On parents' choice of the school travel mode during the covid-19 pandemic, *Math. Biosci. Eng.*, **19** (2022), 9412–9436. https://doi.org/10.3934/mbe.2022438
58. W. Chin, A. Gopal, W. D. Salisbury, Advancing the theory of adaptive structuration: the development of a scale to measure faithfulness of appropriation, *Inf. Syst. Res.*, **8** (1997), 342–367. https://doi.org/10.1287/isre.8.4.342
59. C. Fornell, D. F. Larcker, Evaluating structural equation models with unobservable variables and measurement error. *J. Mark. Res.*, **18** (1981), 39–50. https://doi.org/10.2307/3151312
60. A. García-Ferrer, A. de Juan, P. Poncela, Forecasting traffic accidents using disaggregated data. *Int. J. Forecasting*, **22** (2006), 203–222. https://doi.org/10.1016/j.ijforecast.2005.11.001
61. H. Zhou, S. B. Romero, X. Qin, An extension of the theory of planned behavior to predict pedestrians' violating crossing behavior using structural equation modeling, *Accid. Anal. Prev.*, **95** (2016), 417–424. https://doi.org/10.1016/j.aap.2015.09.009