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The Factors Influencing Resident's Intentions on E-Bike Sharing Usage in China

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Abstract: E-bike sharing is considered a new mode of transport that is rapidly developing in China. In order to better understand the factors affecting the intention to use e-bike sharing, this study is based on the theory of planned behavior (TPB) and the technology acceptance model (TAM) and added the variable of policy support. A sample of 441 respondents in a small city in China was collected to analyze residents' intention on e-bike sharing usage. The results show that the research model can explain well residents' intention to use shared e-bikes. Perceived ease of use, perceived usefulness, attitude, subjective norms, and perceived behavioral control have direct positive effects on the intention to use shared e-bikes. Among them, the perceived ease of use has the greatest impact on the intention to use shared e-bikes. Moreover, policy support has an indirect positive influence on the intention to use shared e-bikes through partial mediation of attitude and subjective norms. Finally, some strategies to promote e-bike sharing are proposed. This study can provide a better understanding of the acceptance of e-bike sharing and the strategy for promoting e-bike sharing in urban transportation.

1. Introduction

With the acceleration of urbanization, problems such as urban road congestion, traffic pollution, and energy consumption are becoming more and more serious [1–3]. Bike-sharing programs seem to be an increasingly popular solution to many transportation sustainability challenges that cities face [4]. Since the first-generation bike-sharing programs were launched in the Netherlands in 1965, the bike-sharing system has evolved to the latest fifth generation of shared e-bike systems [5]. At the same time, academics and mobility experts are also trying to rethink people's transport mode selections by investigating less energy-intensive modes such as the use of e-Powered Micro Personal Mobility Vehicles (e-PMVs) devices [6]. E-bike can be classified as a type of e-PMVs vehicle. The integration of e-bikes with bike sharing can increase the utility of bike sharing [7]. For the latest version of the shared e-bike, users can use the bike by operating a smartphone app. This app can display all the information about the bike, including its current location, charging, and remaining battery life. Compared with previous generations of shared bikes, shared e-bikes are faster, more comfortable, and can cover longer distances.

In recent years, shared e-bikes have become popular all over the world. It is estimated that the global average annual growth rate of the number of e-bike sharing systems in the decade from 2008 to 2018 was 79.3% [8]. Among them, The Chinese market is the fastest growing shared e-bike market in the world [9]; the number of shared e-bikes in China exceeded three million in 2021 [10]. Meanwhile, shared e-bikes have been deployed in more than 300 cities in China, with strong growth potential [11]. This means that shared e-bikes are becoming an important part of transportation in Chinese cities.

In the Quality Development ranking of Chinese Cities in 2021, 337 Chinese cities are divided into first-, second-, third-, and fourth-tier cities according to indicators such as city

size, population, and GDP [12]. Third- and fourth-tier cities generally refer to prefecture-level cities with an average urban size and a population of more than one million in the central urban area. It is worth noting that the shared e-bikes market is mainly concentrated in the third- and fourth-tier cities in China, with fewer in the first- and second-tier cities [10]. This is mainly related to the policies of different cities. Among them, the main reason why shared e-bikes rarely enter the first- and second-tier cities is that these cities have strict policies that discourage the development of e-bike sharing. However, in third- and fourth-tier cities, due to the relative lack of urban public transport facilities and relatively loose policies, the market for shared e-bikes is growing fast.

However, in some places in China, lower satisfaction with e-bike sharing has been seen, and residents lack the intention to use shared e-bikes [13,14]. This may be related to a variety of reasons. Shared e-bikes are a new type of biking device that is still in its infancy. What aspects do urban residents care about, and what factors affect their intention to use? The phenomenon behind this is worth exploring. When we have a deeper understanding of the public's intention to choose e-bike sharing, shared e-bike operators can improve the cycling experience in a more targeted way, local governments can put forward corresponding policies, and residents can better realize low-carbon green travel.

Studies show that residents' attitudes, subjective norms, and perceived behavioral control have a great impact on their intention to adopt bike sharing [15,16]. Further, residents' perceived ease of use and perceived usefulness impose indirect effects on the behavioral intention to use bike sharing [17,18]. Both TPB and TAM evolved from the theory of rational behavior, but the emphasis of the two models is slightly different, which makes the two models mutually compatible and complementary in theory [19]. In addition, policy support has an influence on sharing intention [20]. Previous studies on the intention to use shared e-bikes mostly adopted single model analysis, and the interpretation rate of these models was not high, which could not well explain the resident's intention to use shared e-bikes. There are few studies that systematically investigate whether policy support will affect residents' intention to use shared e-bikes based on the TPB and TAM model. Therefore, based on the TPB and TAM model, this study will add policy support factors to explore residents' intention to use shared e-bikes and test the applicability of the proposed theoretical model in studying the intention to use shared e-bikes.

This study is constructed as follows: Section 2 reviews the relevant literature on shared e-bikes and TPB and TAM theories; Section 3 presents the theoretical framework and research hypotheses. Section 4 focuses on our questionnaire design and data collection. Finally, Section 5 presents the data analysis and the results. Section 6 contains a comprehensive discussion with an explanation of the findings and summarizes this research.

2. Literature Review

2.1. Shared E-Bikes

At present, the coverage of shared travel in China is diversified. The types of shared transportation available to residents include bikes, e-bikes, etc. Shared bikes have a narrow riding range but are cheap. Shared e-bikes can provide a longer riding range and higher speed but are more expensive.

As the city promotes its surrounding "suburban" communities, it introduces new transportation problems that bike shares may not be able to address [9]. For many in these communities, trip lengths have grown to distances requiring motorized solutions [21]. E-bikes could potentially serve as a practical means of transportation for people who live in the suburbs and have a longer commute [22]. Most of the early production of shared e-bikes did not meet China's national standards, posing some safety risks. Until 2019, China issued relevant regulations to standardize shared e-bikes, and then 2020 became the year of the outbreak of shared e-bikes. Riding shared e-bikes takes less effort than regular shared bikes, so shared e-bikes can provide many communities with more options for short and medium trips [23].

The shared e-bikes combine an electric throttle system and a pedal-assist system. These e-bikes provide users with an acceleration device similar to that on the handlebars of a moped, with which the user can adjust the speed of the shared e-bike [24]. The function of the pedal is only used for auxiliary acceleration, and whether it is used or not depends on the user. While power assistance makes riding easier, residents still gain some physical activity benefits by pedaling [25]. After more than a year of practice and research, shared e-bikes have achieved good results in some cities in China, but there are still some problems and contradictions, including inconvenience for users to pick up and return the e-bikes, high use costs, and high cycling risks [10]. Due to the short time of the emergence of shared e-bikes, there are few empirical studies on them.

2.2. The Theory of Planned Behavior

In 1975, American scholars Fishbein and Ajzen first proposed the theory of reasoned action (TRA), which later became the basis of many theories and models of influencing factors of intention [26]. The TPB is based on the evolution and improvement of the TRA, which is a behavior decision model proposed by Icek Ajzen, which is mainly used to predict and understand human behavior [27]. The theoretical model of TPB is widely used and often used to study the problems in the field of transportation. Combined with the actual situation in the field of transportation, the theory is improved and expanded to make the research results more realistic. A study showed that attitudes, subjective norms, and perceived behavioral controls all have significant positive impacts on the intention to adopt bike sharing [16]. These results indicated that TPB is a reliable theory to study the intention of bike-sharing behavior.

2.3. Technology Acceptance Model

Based on the TRA, Davis proposed the TAM in 1986; the purpose is to study the user's acceptance behavior of an information system and analyze which factors determine the user's adoption of the information system [28]. In the TAM model, perceived usefulness and perceived ease of use are the two most important and basic constructs, and they collectively affect the user's attitude [29]. Although perceived usefulness and perceived ease of use act together on attitudes, a large number of studies have shown that the impact of perceived usefulness far exceeds perceived ease of use [30–32]. Nowadays, many scholars have introduced the TAM model into the field of traffic choice behavior, which is used to predict the acceptance of new travel modes by travelers and is widely used to study the factors influencing travelers' intention to use new travel modes [33]. A study showed that perceived ease of use and perceived usefulness could indirectly affect users' intention to use by influencing users' attitudes [17]. However, with the development of society, people's living habits have also changed. In order to improve the interpretation rate of the model, we can combine other factors with TAM to study the use of information systems [34,35].

2.4. Policy Support

As e-bike sharing is an emerging mode of transportation, it is vulnerable to government policies [11]. Different local governments have different attitudes towards e-bike sharing. For example, First-tier cities, such as Beijing and Shanghai, have explicitly discouraged the development of shared e-bikes. However, the third- and fourth-tier cities have relatively loose regulations on shared e-bikes, but they also have requirements on the allocation quota and operation management of shared e-bikes [10]. In a survey on the acceptance of electric vehicle sharing, scholars found that policy support had a significant positive effect on attitudes and subjective norms [20]. These indicate that government policies may have an important impact on residents' intention to use shared e-bikes.

3. Theoretical Framework and Research Hypotheses

Based on the above literature review, as TPB still has limitations in adopting new technologies, we can combine TPB and TAM organically. Therefore, this study combined TPB and TAM models with policy support variables to study residents' intention on e-bike sharing usage and also tested the applicability of the proposed theoretical model in studying the use intention of shared e-bikes. Based on the relationship between variables and structures of the two theoretical models, we propose the hypothesis relationship as shown in Figure 1. The variables in the two theoretical methods are separated by dashed lines, the ellipses represent the potential variables in the theoretical model, and the solid arrows represent the relationships between variables. The specific assumptions are shown below.
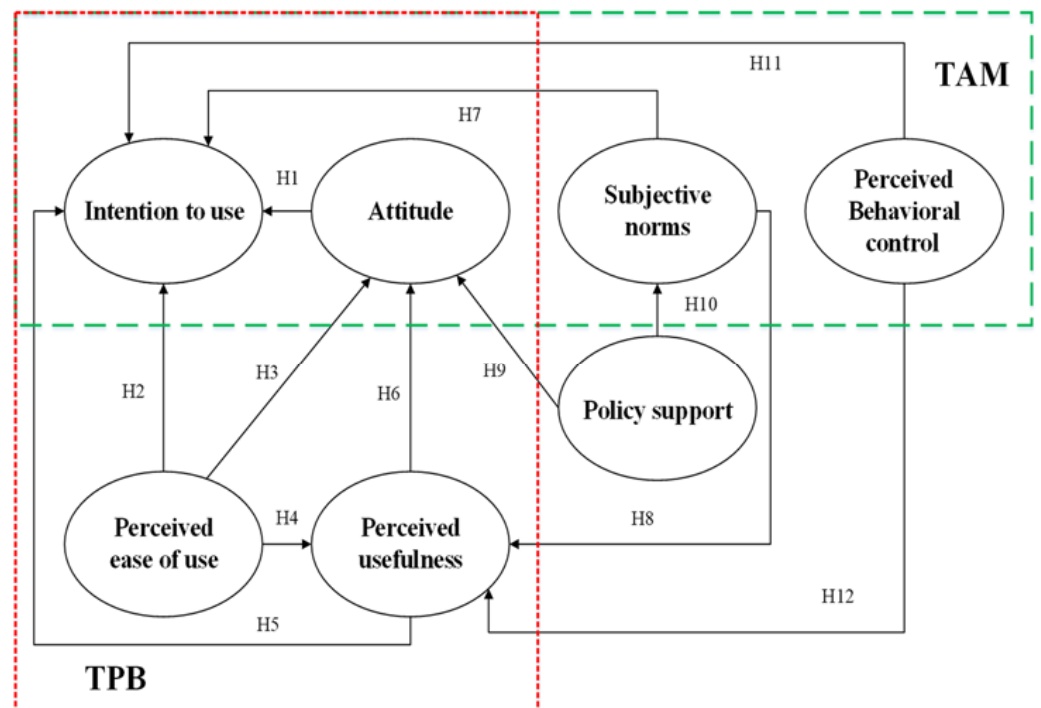

Figure 1. The assumption model of intention to use shared e-bikes.

Behavioral attitude is the subjective attitude of the user to perform this behavior, which refers to the consumer's evaluative statement of using a certain system. It has a causal relationship with choice intention, which has been widely proved in the early TAM theoretical research [36]. That is, it will directly affect users' choice intention. behavioral attitude directly affects the individual's behavioral intention and also indirectly affects the individual's real behavior [30]. Some studies have shown that behavioral attitude can also indirectly affect behavioral intention by influencing moral norms [37,38]. Perceived ease of use is an important variable in the TAM model, which refers to the degree of difficulty for users to operate a specific system when they use it. Perceived ease of use is concretized into perceived ease of rent and return when using shared e-bikes, which reflects the ease of obtaining the right of use when residents need to use e-bikes. Residents only need to scan the QR code with their mobile phones to obtain the system authorization to rent, emphasizing the simplicity of the rental process to obtain the right to use. Some studies show that perceived ease of use positively affects residents' intention to use shared bikes [39].

In the TAM, perceived ease of use directly affects behavioral attitudes. In the evaluation of new technology, perceived ease of use is one of the evaluation criteria, and consumers also want to minimize the effort to use new technology. Consumers, in particular, are concerned not only with the utility of new technology but whether it is easier to use than the technology it replaces. Therefore, perceived ease of use has a positive

impact on attitudes [40]. Perceived ease of use also moderates the indirect influence of behavioral intention through perceived usefulness. Consumers can adjust the utility they derive from using new technology based on how easily they perceive it. Some studies have demonstrated that perceived ease of use has a positive impact on attitude and perceived usefulness [30].

Perceived usefulness is also an important variable in the TAM model. It refers to the degree of performance improvement that users subjectively think it brings when using a specific system. In relation to perceived ease of use, many scholars have defined it in the field of bike sharing, but there is less research in the field of shared e-bikes. Some scholars, in the analysis of the influence factors of bicycle sharing intention, perceived usefulness is defined as the user from bike-share rights of functional benefits [39]. In the field of new technology acceptance, a large number of studies have proved that perceived usefulness has a direct impact on consumers' behavioral items [30,41]. The influence of perceived usefulness on intention to use shared electric bikes can also be adjusted indirectly through attitude. Individuals' positive evaluation of new technology directly affects individuals' acceptance of new technology. Perceived usefulness has been proved to directly affect consumers' attitudes [30].

The decision-making process of users who use or purchase any product or service will be affected by many factors. Subjective norms belong to social influence, which refers to the social pressure that an individual perceives when deciding whether to perform a particular behavior and can be used to predict the intention of the behavior [27]. It reflects the influence of other people or groups on individual behavioral decisions. Some studies have proved that subjective norms have a positive impact on users' choice intention [42].

Perceived behavioral control is a variable in the TPB, and it is also composed of two parts: control beliefs and perceptions about the extent to which a person can control behavior. It is generally defined as the ability of an individual to perceive that he can complete a behavior, that is, a subjective judgment of his ability to complete the behavior. The stronger the individual's perceived behavioral control, the stronger the intention to choose [27].

Hypothesis 1 (H1). *Attitude has a positive effect regarding the intention to use e-bike sharing.*

Hypothesis 2 (H2). *Perceived ease of use has a positive effect regarding the intention to use e-bike sharing.*

Hypothesis 3 (H3). *Perceived ease of use has a positive effect regarding the attitude.*

Hypothesis 4 (H4). *Perceived ease of use has a positive effect regarding the perceived usefulness.*

Hypothesis 5 (H5). *Perceived usefulness has a positive effect regarding the intention to use e-bike sharing.*

Hypothesis 6 (H6). *Perceived usefulness has a positive effect regarding the attitude.*

Hypothesis 7 (H7). *Subjective norms has a positive effect regarding the intention to use e-bike sharing.*

Hypothesis 8 (H8). *Subjective norms has a positive effect regarding the perceived usefulness.*

Hypothesis 9 (H9). *Policy support has a positive effect regarding the attitude.*

Hypothesis 10 (H10). *Policy support has a positive effect regarding the subjective norms.*

Hypothesis 11 (H11). *Perceived Behavioral control has a positive effect regarding the intention to use EBSS.*

Hypothesis 12 (H12). *Perceived Behavioral control has a positive effect regarding the perceived usefulness.*

4. Questionnaire Design and Data Collection

4.1. Questionnaire Design

The questionnaire was designed by referring to relevant literature [11,17,43,44]. The survey was carried out by randomly issuing paper questionnaires. In order to ensure that the respondents have used shared e-bikes, the respondents should be asked if they have used shared e-bikes before filling in the questionnaire. If the respondents answer no, the questionnaire will be ended.

Previous studies have found that TPB and TAM model has strong applicability in many fields of intention research [17,44]. Therefore, this study will add policy support variables on the basis of the TPB and TAM model, hoping to obtain better model prediction ability. The questionnaire consists of two parts: demographic information and a combined TPB and TAM scale. The demographic information included age, gender, occupation, education, and monthly income. The combined TPB and TAM scale consists of the TPB and TAM scale and policy support scale, with a total of seven variables, including: Perceived Ease of Use (PE), Perceived Usefulness (PU), Policy Support (PS), Behavioral Attitude (BA), Subjective Norms (SN), Perceive Behavioral Control (BC) and Intention to Use (IU). The scale items of variables were adapted from the existing scales of previous works [11,17,20,43,45]. In this part, respondents rated their opinions on a five-point Likert scale of 1 (strongly disagree), 2 (disagree), 3 (neutral), 4 (agree), and 5 (strongly agree). On the basis of consultations with experts and small-scale tests, the initial questionnaire was revised to become the final questionnaire. The specific items are shown in Table 1.

4.2. Data Collection

In order to obtain a sufficient survey sample size, our research will study the market of e-bike sharing in China. In 2020, a large number of sharing e-bikes entered the third- and fourth-tier cities in China, which account for more than 70% of China's users [46]. Guangdong province has the best economy and the largest population in China, and Shaoguan city, as a typical fourth-tier city in Guangdong province, is also a transportation hub city, and a questionnaire survey will be conducted on the urban residents in Shaoguan. According to the Communiqué of the Seventh Chinese Census, the population of the main urban area of Shaoguan is 1,028,460 [47]. Shaoguan city covers an urban area of about 60 square kilometers. At present, there is a total of more than ten thousand shared electric bikes in the urban area of Shaoguan put into use. In Shaoguan, the distribution of shared e-bikes is mainly concentrated in the central urban areas and places with dense traffic. In this study, the residents of the Shaoguan urban area who have used shared e-bikes were randomly surveyed by face-to-face questionnaire. The questionnaire was collected from January to February, 2022. A total of 470 questionnaires were collected, of which 441 were valid.

The demographic information of age, gender, occupation, education level, and monthly income of the respondents are shown in Table 2. In terms of age, respondents aged between 18 and 60 accounted for the majority (83.45%). Men accounted for 58.5 percent of all respondents, slightly more than women. A total of 50.79% of the respondents were employees of government agencies, enterprises, and public institutions (including lecturers), indicating that shared bikes were favored by office workers. In addition, 68.71 percent of the respondents have a bachelor's degree or above, and 63.27 percent have a monthly income of more than CNY 5000. This shows that shared e-bikes are more favored by middle and high education and income groups. In general, the structural characteristics of the respondents in this study are similar to the "2020 Special Report on Safety Management of Shared Electric Bicycles in China" by iiMedia Research, which confirms the good representativeness of the samples in this study.

Table 1. Items in the five subscales of E-bike sharing intention.

Variables	Observation Item	Label
Perceived Ease of Use	it's easy for me to register as shared e-bike users.	PE1
	It's easy for me to find and unlock the shared e-bikes.	PE2
	It's easy for me to park the shared e-bikes.	PE3
	It's easy for me to pay for the shared e-bikes.	PE4
Perceived Usefulness	Using the shared e-bikes can save time.	PU1
	Using the shared e-bikes can save resources.	PU2
	Using the shared e-bikes can protect the environment.	PU3
	Using the shared e-bikes can reduce the traffic congestion.	PU4
	Using the shared e-bikes can enhance travel efficiency.	PU5
Policy Support	Governmental restrictions on private car lead me to use shared e-bikes.	PS1
	Governmental restrictions on exceeding electric bikes lead me to use shared e-bikes.	PS2
	Governmental policy support for shared e-bike lead me to use shared e-bikes.	PS3
	Governmental planning and management of shared e-bike lead me to use shared e-bikes.	PS4
Behavioral Attitude	It is convenient to use the shared e-bikes.	BA1
	It is comfortable to use the shared e-bikes.	BA2
	It is interesting to use the shared e-bikes.	BA3
	It is valuable to use the shared e-bikes.	BA4
Subjective Norms	Media coverage can influence my choice to shared e-bikes.	SN1
	My schoolmates or workmates can influence my choice to shared e-bikes.	SN2
		SN3
	My friends can influence my choice to shared e-bikes.	SN4
	My family members can influence my choice to shared e-bikes.	
Perceive Behavioral Control	I have the skills to ride shared e-bikes.	BC1
	I have the knowledge to use e-bike sharing app.	BC2
	I have the physical quality to use shared e-bikes.	BC3
	I have the psychological quality to deal with riding risks.	BC4
Intention to Use	I will continue to use shared e-bikes.	IU1
	I will recommend others to use shared e-bikes.	IU2
	I intend to use shared e-bikes as a feasible way to travel in the future.	IU3
	In the future, I will choose to use shared e-bikes if needed.	IU4

Table 2. Demographics and relevant frequency statistics.

Characteristic	Demographics	Frequency	%
Age	Under 18	43	9.75
	18–30	162	36.74
	31–45	130	29.48
	46–60	76	17.23
	Over 60	30	6.80
Gender	Male	258	58.50
	Female	183	41.50
Occupation	Student	104	23.58
	Lecturers	78	17.69
	Personnel of government and public institutions	70	15.87
	Enterprise staff	76	17.23
	Freelancer	62	14.06
Education level	Below associate degree	64	14.51
	Associate degree	74	16.78
	Bachelor degree	198	44.90
	Master degree	66	14.97
	PhD	39	8.84
Personal income (monthly)	Less than RMB 3000	120	27.21
	RMB 3000–5000	42	9.52
	RMB 5001–8000	133	30.16
	RMB 8001–12,000	90	20.41
	More than RMB 12,000	56	12.70

5. Data Analysis and Results

5.1. Reliability and Validity Analysis

In order to verify the reliability of the data collected from the questionnaire, a reliability analysis of the collected data was carried out in this study. Cronbach's α was used to evaluate the reliability of the collected data, which are also the most commonly used reliability test indexes at present. As shown in Table 3, Cronbach's α values of each variable were all greater than 0.8, indicating that the questionnaire had high reliability. The standard factor load of each measurement item was all greater than 0.5, indicating that the scale has good internal consistency.

In a validity analysis, convergence validity and discriminant validity are often used to measure the validity of each variable. As can be seen from Table 3, AVE (average variance extracted) values of all variables are greater than 0.50, and CR (compound reliability) values are greater than 0.7. It is considered that the questionnaire has good reliability and convergence validity. From Table 4, the diagonals in the table are AVE square root values, and the other values are correlation coefficients. The AVE square root values of each variable are greater than the absolute values of correlation coefficients with other variables, indicating that the questionnaire has good discriminating validity.

5.2. Model Goodness-of-Fit Testing

The goodness of fit of the model was evaluated by nine specific indexes: chi-square freedom degree ratio (c2/df), the root-mean-square-error of approximation (RMSEA), the standardized root-mean-square residual (SRMR), the goodness-of-fit index (GFI), the adjusted goodness of fit index (AGFI), the comparative fit index (CFI), and the Tacker—Lewis Index (TLI), normed fit index (NFI) and incremental fit index (IFI). The indices are computed using AMOS 23.0. AMOS is a software developed by IBM in the United States for processing structural equation model (SEM). The fitting indexes of the model are all in the ideal range, indicating that the model fitting degree is high, as shown in Table 5.

Table 3. Results of confirmatory factor analysis.

Variables	Label	Cronbach's α	AVE	CR	Standard Factor Load
Perceived Ease of Use (PE)	PE1 PE2 PE3 PE4	0.875	0.638	0.875	0.786 0.849 0.788 0.768
Perceived Usefulness (PU)	PU1 PU2 PU3 PU4 PU5	0.870	0.574	0.870	0.703 0.816 0.762 0.747 0.755
Policy Support (PS)	PS1 PS2 PS3 PS4	0.860	0.606	0.860	0.772 0.798 0.773 0.770
Behavioral Attitude (BA)	BA1 BA2 BA3 BA4	0.861	0.605	0.860	0.775 0.818 0.737 0.779
Subjective Norms (SN)	SN1 SN2 SN3 SN4	0.861	0.609	0.862	0.761 0.806 0.759 0.794
Perceive Behavioral Control (BC)	BC1 BC2 BC3 BC4	0.850	0.588	0.851	0.812 0.722 0.743 0.786
Intention to Use (IU)	IU1 IU2 IU3 IU4	0.875	0.643	0.878	0.776 0.793 0.761 0.872

Table 4. Discriminant validity of variables.

Variable	PE	PU	PS	BA	SN	BC	IU
PE	0.799	-	-	-	-	-	-
PU	0.400	0.758	-	-	-	-	-
PS	0.064	0.139	0.778	-	-	-	-
BA	0.312	0.477	0.378	0.778	-	-	-
SN	0.068	0.250	0.428	0.283	0.780	-	-
BC	0.033	0.294	0.023	0.135	0.086	0.766	-
IU	0.484	0.646	0.236	0.571	0.430	0.442	0.802

Table 5. Model fitting indexes of the model and recommended standards.

Fitting Index	c2/df	RMSEA	SRMR	GFI	AGFI	CFI	TLI	NFI	IFI
Ideal Value	1~3	<0.05	<0.05	>0.90	>0.90	>0.90	>0.90	>0.90	>0.90
Experimental Value	1.461	0.032	0.042	0.929	0.916	0.976	0.973	0.927	0.976

5.3. Path Analysis and Hypothesis Testing

AMOS 23.0 was used for path analysis to obtain standardized regression weights and hypothesis results among variables, as shown in Table 6 below. The standardized path coefficients between all paths are greater than 0.1 and are significant below the 1% level, indicating that all hypotheses are valid.

Table 6. Path coefficients of the structural model.

Path	Standard Path Coefficient	T-Values	p-Values	Hypotheses	Result
BA→IU	0.262	6.079	3.67×10^{-9}	H1	Valid
PE→IU	0.304	7.426	1.17×10^{-12}	H2	Valid
PE→BA	0.139	2.664	8.14×10^{-3}	H3	Valid
PE→PU	0.438	8.081	1.59×10^{-14}	H4	Valid
PU→IU	0.286	5.801	1.67×10^{-8}	H5	Valid
PU→BA	0.434	7.381	1.55×10^{-12}	H6	Valid
SN→IU	0.285	7.615	3.46×10^{-13}	H7	Valid
SN→PU	0.237	4.804	2.46×10^{-6}	H8	Valid
PS→BA	0.362	7.236	3.88×10^{-12}	H9	Valid
PS→SN	0.492	8.719	1.95×10^{-16}	H10	Valid
BC→IU	0.353	8.955	3.66×10^{-17}	H11	Valid
BC→PU	0.306	6.005	5.52×10^{-9}	H12	Valid

Table 7 shows the standard direct, standard indirect, and standard total effects of the different variables on behavioral intention. The contribution of different variables to intention to use is ranked in order of importance as follows: Perceived Ease of Use (0.516), Perceived Behavioral Control (0.476), Perceived Usefulness (0.400), Subjective Norms (0.380), and Policy Support (0.282) and Behavioral Attitude (0.262). Policy support has an indirect impact on behavioral intention, with an impact value of 0.282, and has a direct impact on behavioral attitude and subjective norms, with an impact value of 0.362 and 0.492, respectively.

Table 7. Effects of different variables on the intention to use shared e-bikes.

Variables	Standard Direct Effect	Standard Indirect Effect	Standard Total Effect
Perceived Ease of Use	0.304	0.212	0.516
Perceived Usefulness	0.286	0.114	0.400
Policy Support	-	0.282	0.282
Behavioral Attitude	0.262	-	0.262
Subjective Norms	0.285	0.095	0.380
Perceive Behavioral Control	0.353	0.123	0.476

Figure 2 shows the marginal effect of each variable on the intention to use shared motorcycles. The average marginal effects of PE, PU, PS, BA, SN and BC were 0.2577, 0.2884, −0.0328, 0.2231, 0.2567 and 0.2842, respectively. The larger the average marginal effect value of the variable, the greater the intention of residents to use shared e-bikes when the variable improves.
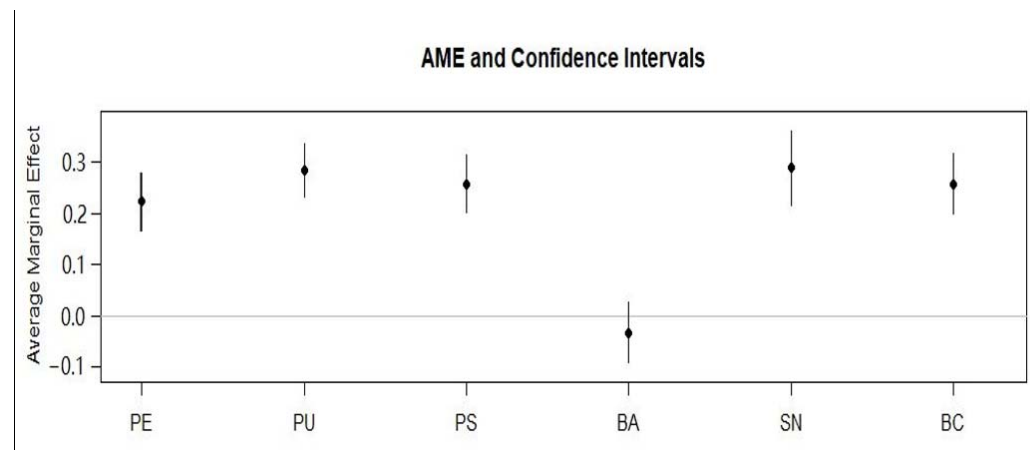
Figure 2. Marginal effect for variables.

This study mainly explains residents' intention to use shared e-bikes through the combined TPB and TAM model. The SEM of residents' e-bike sharing intention is shown in Figure 3. This is a flow chart of an SEM with coefficients calculated. In AMOS, rectangles represent observed items, ellipses represent variables, circles represent residuals, and single arrows represent causal relationships. Relationships between variables are represented by line segments, and if there is no line between two variables, it means that there is no direct relationship between the two variables. The arrow on the line segment points to one variable, indicating that the variable is affected by another variable. At this point, if the line segments connect the effects between the observed items and the variables, the numbers on the line segments represent factor loadings; if the line segments connect the relationships between variables, the numbers on the line segments represent the path coefficients.
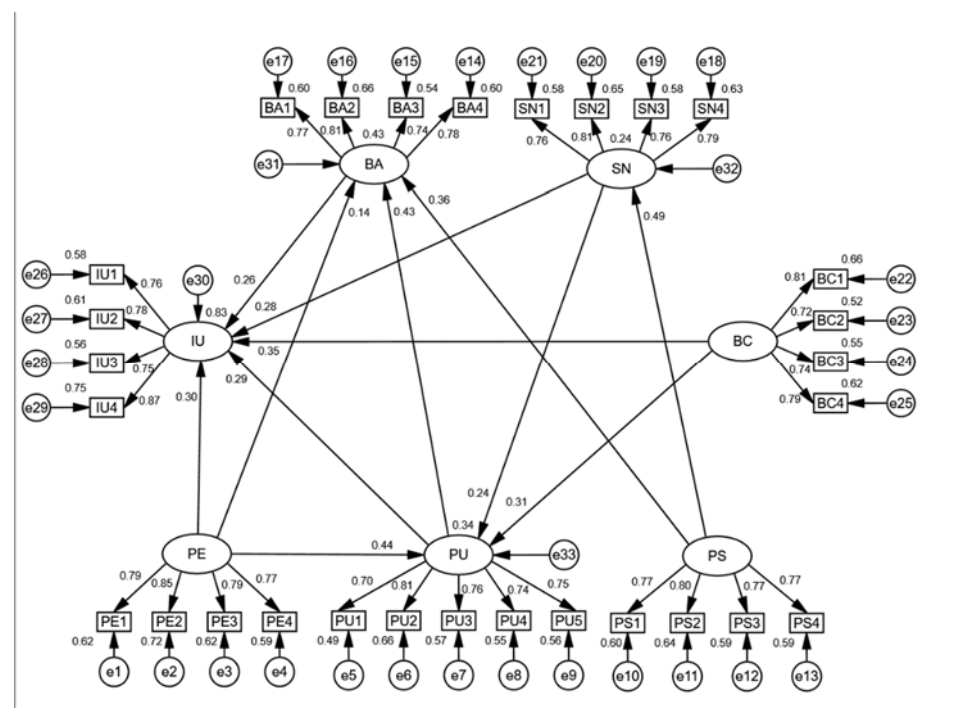

Figure 3. Structural equation model of residents' e-bike sharing intention.

According to the analysis results of SEM, behavioral attitude, subjective norms, perceived behavioral control, perceived usefulness, perceived ease of use, and policy support all have a positive impact on the intention to use shared e-bikes. Among them, perceived

ease of use has the greatest impact on intention to use shared e-bikes, followed by perceived behavioral control, perceived usefulness, subjective norms, policy support, and behavioral attitude. In addition, From the value of R_2, our combined TPB and TAM research model can explain the variance of 82.5% of residents' intention to use shared e-bikes, indicating that the model has sufficient predictive power.

5.4. Discussion

Perceived ease of use has the greatest impact on behavioral intention, which indicates that residents' ease of use of shared e-bikes will greatly affect residents' intention to use shared e-bikes. As a new mode of travel, it is important for many residents to be able to use shared e-bikes easily. Therefore, the operators of shared e-bikes should put forward corresponding measures to simplify the use of shared e-bikes and reduce their difficulty of use.

Perceived usefulness can also affect behavioral intention, which means that residents can not only exercise but also save resources, protect the environment, alleviate traffic congestion and improve travel efficiency when using shared e-bikes. Residents are also more willing to use shared e-bikes due to their multiple benefits. This shows that residents' awareness of green travel is high. It is suggested that operators increase the release of shared e-bikes in the future to promote the healthy development of transportation.

Behavioral attitudes have a certain influence on behavioral intentions, mainly because shared e-bikes are convenient, comfortable, interesting, and valuable. Residents show a positive attitude towards the use of shared e-bikes, among which convenience and comfort have the most significant impact, which is closely related to the service quality provided by shared e-bike operators. It is suggested that operators can improve the configuration of shared e-bikes and designate the parking spots suitable for residents to pick and park, which will help increase the public's intention to use shared e-bikes.

Subjective norms also play an important role in influencing behavioral intention, which indicates that social media and the opinions of people around will both affect the behavioral choice of e-bike sharing because the behavioral intention of individuals tends to be consistent with the people around them or they will appear to be incompatible. Therefore, operators should increase the positive publicity of shared e-bikes to improve the radiation effect on potential users.

Perceived behavioral control can affect behavioral intention to a great extent, including physical quality, psychological quality, mobile phone operation skills, and riding skills, which can have a positive impact on the public's choice of shared e-bikes. It is suggested that operators can continuously improve users' riding experience and reduce the safety risks of shared e-bikes.

Behavioral attitude and subjective norms play a mediating role in the influence of policy support on behavioral intention. In other words, policy support can broadly influence residents' intention to share e-bikes through subjective norms and perceived attitudes. This shows that proactive policies can improve public attitudes and intention to use share e-bikes. Therefore, we hope that the government will introduce more policies to support the development of shared e-bikes in the future so as to increase the possibility for residents to participate in shared e-bikes.

As the first attempt to investigate the residents' intention toward shared e-bikes through a combined TPB and TAM model, the findings of the current study have some important practical implications for promoting residents' participation behavior. First of all, the results of this study can provide theoretical guidance for e-bike sharing operators in product design and publicity strategy. At present, the product design of shared e-bikes still needs to be optimized, and the information publicity to guide users to participate in e-bike sharing is not enough. In addition, it also provides theoretical support for the government to better introduce relevant policies. Finally, this combined TPB and TAM model can also be applied to other studies on shared intention in the academic field.

6. Conclusions

In this study, a combined TPB and TAM model was established to verify the influence mechanism of perceived ease of use, perceived usefulness, behavioral attitude, subjective norms, perceived behavioral control, and policy support on intention to use shared e-bikes. Perceived ease of use, perceived usefulness, attitude, subjective norms, and perceived behavioral control have a direct positive impact on the intention to use shared e-bikes. Among them, perceived ease of use has the greatest impact on intention to use shared e-bikes, while behavioral attitude has the least impact on willingness to use shared e-bikes. In addition, policy support has an indirect positive impact on the intention to use shared e-bikes through the partial mediating role of attitude and subjective norms. It is an effective way to introduce relevant policies for the development of shared e-bikes, such as restricting the trips exceeding e-bikes or providing financial subsidies to shared e-bike operators.

The findings from this study make several contributions to the current literature. First, this study extends the application scope of a combined TPB and TAM model to the research field of e-bike sharing intention for the first time. Second, this study found that the combined TPB and TAM model has a high explanatory degree ($R_2 = 82.5\%$), which is higher than a single use of the TPB and TAM model, indicating that this model can well explain residents' intention to use shared e-bikes. Third, this study also puts forward some suggestions to support the sustainable development of shared e-bikes in China.

The limitations of this study can be addressed in the scope of future work. Firstly, since e-bike sharing is a new and innovative mode of travel choice, individuals' behavior will also be influenced by the resources of shared e-bikes around them. With the mass rollout of e-bikes in the future, residents' perceptions of e-bike sharing may change accordingly. Therefore, the model should be combined with user preference survey data in order to accurately explain residents' travel behavior. In future studies, we can extend the study period and conduct comparative analysis. Secondly, this study only describes several variables to construct SEM. Future studies should include more demographic information in SEM, such as gender, age, income, occupation, education background, etc., so as to process multiple variable analyses simultaneously. Third, the research area is in the third-tier and fourth-tier cities in southern China. Whether the research conclusion can be replicated in the third-tier and fourth-tier cities in northern China needs further study.

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