

Article

Mixed Logit Models for Travelers' Mode Shifting Considering Bike-Sharing

Mao Ye ^{1,*} , Yajing Chen ¹, Guixin Yang ², Bo Wang ¹ and Qizhou Hu ¹

¹ Traffic Engineering Department, Nanjing University of Science and Technology, Nanjing 210094, China; 18362902563@163.com (Y.C.); aisijimewb@163.com (B.W.); qizhouhu@163.com (Q.H.)

² Transport Authority of Transport Department of Jiangsu Province, Nanjing 210094, China; ygx@jscd.gov.cn

* Correspondence: yemao0924@163.com; Tel.: +86-1385-229-8470

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Abstract: This study quantifies the impact of individual attributes, the built environment, and travel characteristics on the use of bike-sharing and the willingness of shifting to bike-sharing-related travel modes (bike-sharing combined with other public transportation modes such as bus and subway) under different scenarios. The data are from an RP (Revealed Preference) survey and SP (Stated Preference) survey in Nanjing, China. Three mixed logit models are established: an individual attribute–travel characteristics model, a various-factor bike-sharing usage frequency model, and a mixed scenario–transfer willingness model. It is found that age and income are negatively associated with bike-sharing usage; the transfer distance (about 1 km), owning no car, students, and enterprises are positively associated with bike-sharing usage; both weather and travel distance have a significant negative impact on mode shifting. The research conclusions can provide a reference for the formulation of urban transportation policies, the daily operation scheduling, and service optimization of bike-sharing.

Keywords: bike-sharing; travel mode transfer; travel willingness; influencing factors; mixed logit model

1. Introduction

The development of technologies such as big data and mobile payments has led to new types of travel, including bike-sharing. Bike-sharing is where companies provide bicycle-sharing services in public service areas such as campuses and subway stations. It is a time-sharing leasing model, which is in line with the concept of low-carbon travel, maximizes the use of public road passing rates, and is a new type of green environmental protection sharing economy. Currently, the most widely used bike-sharing systems are the traditional docked bike-sharing systems (public bike-sharing systems) and the new dockless bike-sharing systems. The new dockless bike-sharing is formed by the development of public bicycles.

Bike-sharing services are provided in more than 400 regions around the world [1]. China is undoubtedly the largest market, as the founding country of the new dockless bike-sharing [2]. The fastest growing year for users in the bike-sharing industry in China was 2017, with a growth rate of 632.1%. By the end of 2017, China had 16 million bike-sharing users. In addition, the total cycling distance of bike-sharing exceeded 29.947 billion kilometers, and the number of users exceeded 205 million. Although there was a phenomenon of capital withdrawal and industrial recycling in the bike-sharing industry in 2018, the number of users sharing bicycles still reached 235 million, with a growth rate of 14.6% [3].

The booming use of bike-sharing has enriched residents' travel modes, revived the slump of bicycle travel caused by rapid economic development, maximized the use of public road passing rates,

and increased the possibility of combining bike-sharing and public transportation. According to the existing research, the factors that influence the travel mode choice and transfer of travelers include personal attributes [4], family attributes [5], traffic characteristics [6], and travelers' attitudes [7]; these factors have been identified via discrete choice models and machine learning models [8–11]. In the study of the shifting of travel modes, there are many studies on the transfer of cars to public transport (especially rail transit) [12,13]. Regarding the shift of bike-sharing modes, existing studies are mostly aimed at analyzing the proportion of bike-sharing replacing other modes of travel [14,15]. Research relating to mode shift willingness has not yet emerged for a mixed scenario with multiple factors.

Therefore, this study starts with this point, and uses the travel chain that combines bike-sharing and other public transportation modes (bus and subway) as the research object, and discusses the impact of the introduction of bike-sharing on the travel mode of travelers and mode shift willingness. A discrete selection model is considered. The standard logit model is limited by the IIA (the Independence of Irrelevant) conditions, which include random error limits (independence and equivalent distributions). The factors affecting travel mode shifting are not unrelated, so the standard logit model does not apply. The utility function of the mixed logit model adds an error term that allows for correlation between the choices, which solves the problem of IIA [16]. Considering that the mixed logit model does not require the IIA, three models are built using this method.

The paper establishes an individual attribute–travel feature model and analyzes the influence of the individual attributes on travel characteristics when using bike-sharing-related travel modes. A various-factor bike-sharing usage frequency model is established to explore the impact of traveler's individual attributes, built environment, and travel characteristics on the number of bike-sharing used. We have established a mixed scenario–transfer willingness model to investigate the tendency of travelers to shift to bike-sharing-related travel modes in different scenarios. Based on the research findings, the degree of influence of various types of travelers is clearly identified, which provides a reference for urban traffic policy formulation and bike-sharing operation management, daily dispatch, and structural optimization, and promotes the organic integration of multi-modal transportation modes for efficient and green development of the comprehensive urban transportation system.

The remainder of this paper is organized as follows. Section 2 is a literature review. Section 3 is the data collection and description. Section 4 introduces the research methods of the paper. Section 5 discusses the model results. Section 6 is the main results summary.

2. Literature Review

Bike-sharing combines traditional bicycle travel with modern mobile payment and network technology to form an efficient, convenient, and environmentally friendly mode of transportation. Bike-sharing is generally operated by governments or private companies and is classified into the public transportation system [17]. As an "active way of travel," bike-sharing travel can not only promote urban transport sustainability by reducing traffic congestion and emissions, but also help to improve human health [18]. With the development of the emerging sharing economy, bike-sharing services are increasingly attracting the attention of researchers, policy makers, and social marketers [19,20]. Existing studies have mainly analyzed the travel characteristics based on travel speed and travel time [21,22] and the purpose of shared bicycle travel [23], or studied the impact of gender on travel behavior based on visualization technology [24]. These studies are mainly based on movement and ignore the transitional activities between successive trips in the travel chain.

Studies show that after the introduction of bike-sharing, the number of cycling activities in some cities (such as Washington, DC, USA, Lyon, Paris, and Barcelona) has increased, which indicates that travelers have moved from other modes of bike-sharing [12,13]. For example, 85% of bike-sharing users (respondents) in Dublin shifted from walking and public transportation [14]. In Beijing, 22.73% and 34.42% of bike-sharing trips shifted from walking and bus, and 26.159% and 40.37% of Shanghai bike-sharing trips shifted from pedestrian and public buses, respectively [15]. About 80% of Hangzhou shared bicycle users (respondents) switched from public transportation to bike-sharing [13]. Although

most travelers who are attracted to bike-sharing shift from other sustainable modes, this is not a desirable green policy outcome.

Habib et al. selected expectations, comfort, and safety awareness as influencing factors to study regarding bicycle travel needs, and they found that owning a bicycle and having safety awareness had a positive impact on the bicycle mode. Older men and younger women have higher requirements for comfort in the travel process, which has an impact on the choice of bicycle travel [4]. Rubin et al. analyzed the factors on their travel mode choice by families, and the results showed that family structure and vehicle ownership rate are the main factors [5]. Habib and Weiss conducted a survey of Toronto residents, and proposed that the behavior of residents has a significant impact on the travel mode selection behavior [25]. Parody et al. analyzed cross-sectional data to explore the causal relationship between the built environment and travel behavior, and the existence of a causal mode substitution mechanism between cars and non-motorized modes, given increases in the urbanization level at residential locations [6].

Multiple studies show that males and those aged 20–40 years have a higher probability of bike-sharing [26–28]. A station pair (origin–destination (OD)) regression model was developed based on station to station path level service attributes, along with other zonal level factors [29]. The above research results, on the choice of travel mode, show that the factors on travel mode choice are mainly divided into four categories: personal attributes, family attributes, built environment, and traffic characteristics. Among them, the personal attributes include gender, age, education level, income, occupation, etc.; the family attributes include whether or not to own a private car, etc.; the built environment refers to the distance between stations; and travel characteristics includes travel purposes, travel distance, travel time, travel expenses, etc.

Residents' behavior is often influenced by their attitudes. According to the theory of planned behavior, residents' attitudes have a significant impact on behavioral intentions, and behavioral intentions have a significant impact on their actual behavior [7]. Therefore, research attitudes are important for the impact of travel mode choices. Liuet al. proposed that low-carbon awareness indirectly affects travelers' low-carbon travel intentions [30]. Jiaet al. pointed out that attitudes and low-carbon factors influence the behavioral intention of travel mode choice [31]. The existing studies have identified the importance of social and personal attitudes towards bike-sharing intentions [32].

In recent years, many analytical methods have been applied to travel behavior analysis, including descriptive analysis and advanced statistical and machine learning models such as multinomial logit [8], nested logit [8], cross-nested logit [10], and random forest [11]. Most studies used discrete choice models to describe the traveler's mode choice mechanism based on traveler survey data. Domarchi et al. established a multinomial logit model and introduced dummy variables representing attitude factors to explore the impact of potential psychological factors on travel choices [33]. Arman et al. used a two-level mixed nested logit model to analyze the travel patterns of Iranian women [34]. The mixed logit model is one of the discrete choice models, compared to other logit models, and is not subject to IIA conditions [16]. This model can simulate any kind of discrete selection model (including logit, probit, nested logit, etc.) and has the advantage of being able to consider the difference in preferences of individuals [35,36].

To summarize, the existing research mainly focuses on the study of single shared bicycle travel and the proportion of other travel modes shifting to bike-sharing in various regions, without considering the willingness of travelers to shift to bike-sharing in different travel scenarios (including weather, travel period, travel purposes, etc.). In different travel scenarios, travelers have different degrees of willingness to choose bike-sharing as a travel mode, due to their different attributes and consideration of scene factors. Therefore, this study considers bike-sharing-related travel modes (bike-sharing or bike-sharing plus the bus and subway). The study selected several factors of individual attributes, travel characteristics, and the built environment, setting up different travel scenarios and using the survey data to conduct mixed logit modeling. Taking into account the individual preferences of respondents, this paper analyzes the impact of a traveler's personal attributes, built-up environment,

and travel characteristics on the use of shared bicycle frequencies, as well as the degree of willingness of travelers to shift to bike-sharing-related travel modes under different scenarios.

3. Data and Variables

3.1. Travel Survey

The online survey was conducted in Nanjing, China, in September 2018, and two offline supplementary surveys were conducted in January 2019 and September 2019, which were implemented by Revealed Preference (RP) survey. An online survey is a function that has only emerged in recent years. At present, these are only widely popular among young people and some middle-aged groups who are in close contact with network development. This survey is aimed at all travelers (>12 years) who are able to use bike-sharing; therefore, middle-aged and elderly groups are also a key part of the survey. If only the online survey method is used, there will be the following problems: 1. Surveys will be lacking for older people who use the Internet less; 2. For those who are not familiar with the online survey operation, they will lack patience and participation interest. Therefore, online surveys that rely solely on smart phone usage can produce biased samples.

In the end, the survey was conducted both online and offline. In the first stage, online surveys were distributed via WeChat (friend sharing) and emails, and questionnaires were collected through the platform. In the second stage, after a simple analysis of the questionnaires collected online, it was found that the number of recycling questionnaires for the elderly was small. Supermarkets, community plazas, shopping malls, and other crowded places were selected, and paper questionnaires were distributed to people who are older and unfamiliar with mobile devices.

The questionnaire of the study mainly included the following three aspects:

1. Travelers' individual attributes Due to the differences in travel behaviors of different groups of people, it was necessary to investigate the personal attributes of the travelers, including the gender, age, occupation, education, personal monthly income, and whether they own cars.
2. Travelers' travel characteristics This part was a survey of travelers' travel characteristics, including the number of times bike-sharing was used in a week, travel time (time spent on a trip chain), travel expense, and travel distance of the last travel chain using a bike-sharing-related travel mode, the importance of time savings, whether it was economical, comfortable, and environmentally friendly, and the impact of the built environment (the distance to transfer using bike-sharing when using public transportation, which was expressed as the "distance between site and destination") in order to obtain a large number of travel characteristics.
3. Travelers' willingness to shift to bike-sharing-related travel modes This was the key content of the questionnaire. Through the Stated Preference (SP) survey, the travelers' intentions and acceptance attitudes were obtained for the new method of bike-sharing, so as to predict the changes and impacts brought by it. Four impact factors, including the weather, travel time, travel destination, and travel distance, were selected to design 24 hypothetical scenarios, which ensured that the hypothetical scenario completely covered every possible scenario. For example: on a sunny day, when commuting during peak hours, and over a short distance (<3 km), the willingness to choose bike-sharing-related travel modes is: 1. Completely unwilling; 2. Not willing; 3. Generally willing; 4. More willing; 5. Very willing.

We collected 1247 valid online questionnaires, and 398 valid questionnaires were collected from the two offline surveys. Thus, 1645 valid samples were used for modeling.

3.2. Analysis of Influencing Factors

A mixed logit model was established based on the individual attributes of travelers. Independent variables included: gender, age, education, occupation, personal monthly income, and car ownership. The travel time and travel expense in the travel characteristics were dependent variables. The model

aimed to study whether the individual attribute variables would affect travel time and travel expenses on bike-sharing-related trips, and to analyze the variables that had a significant influence.

The individual attributes, the built environment, and travel characteristics were selected as independent variables, and the number of travelers using bike-sharing was the dependent variable to determine whether each factor would affect the frequency of using bike-sharing. Travel weather, travel time, travel purpose, and distance were selected as independent variables. Transfer willingness was a dependent variable, and a mixed logit model was established to study the willingness to shift. Variable selection, descriptions, and the statistic results are shown in Tables 1–4, and Figure 1, respectively.

Table 1. Individual attribute statistics of the sample.

Survey Project	Variable	Variable Description	Number of Samples	Proportion/%
Gender	a1	0: Man	872	53.0%
		1: Woman	773	47.0%
Age (years)	a2	0: 12–30	1153	70.1%
		1: 31–50	409	24.9%
		2: >50	83	5.0%
Education	a3	1: High school/former	279	17.0%
		2: Undergraduate/college	691	42.0%
		3: Master/above	675	41.0%
Occupation	a4	1: Student	775	47.0%
		2: Institution staff	241	14.7%
		3: Business employee	333	20.2%
		4: Self-employed	67	4.1%
		5: Retiree	39	2.4%
		6: other	190	11.6%
Monthly income	a5	0: <¥2000	671	40.8%
		1: ¥2000–¥5000	497	30.2%
		2: ¥5000–¥10,000	378	23.0%
		3: >¥10,000	99	6.0%
Car ownership	a6	0: yes	349	21.2%
		1: no	1296	78.8%

Note: “Institution staff” means a person working in an institution. Institution refers to departments or units that are under the leadership of state organs, which is in contrast to “enterprise units.” For example, schools, hospitals, and some research institutes belong to public institutions.

Table 2. Built environment statistics of the sample.

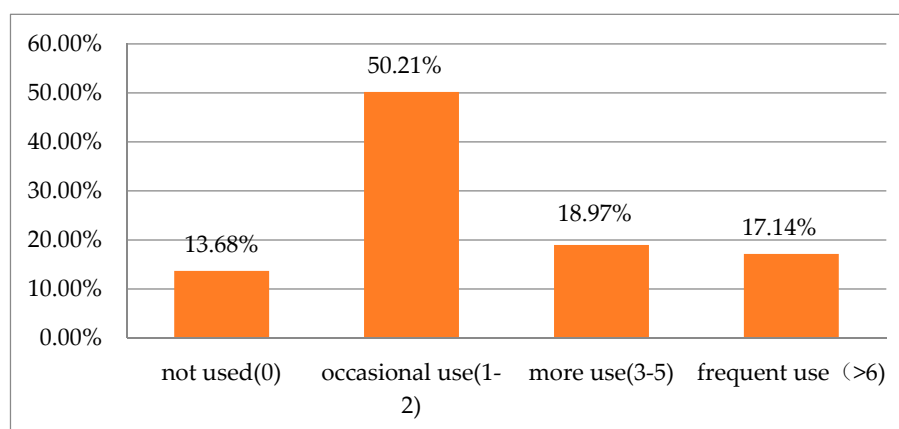
Survey Project	Variable	Variable Description	Number of Samples	Proportion/%
Distance between site and destination	b1	1: 500m	479	29.1%
		2: 800m	324	19.7%
		3: 1000m	576	35.0%
		4: 1500m	266	16.2%

Table 3. Travel characteristic statistics of the sample.

Survey Project	Variable	Variable Description	Number of Samples	Proportion/%
Travel time	c1	0: 0–30 min	1155	70.2%
		1: 30–60 min	302	18.4%
		2: >60 min	188	11.4%
Travel expense	c2	0: <¥1	988	60.1%
		1: ¥1–¥4	558	33.9%
		2: >¥4	99	6.0%
Travel preference	c3	Time saving c31	1434	
		Economic c32	1136	
		Comfort c33	860	
		Environmentally friendly c34	503	
		Safety c35	813	

Table 4. Twenty-four hypothetical scenarios.

Hypothetical Scenarios	
1	Sunny weather, Peak congestion period, Commuting travel, Short-distance (<3 km)
2	Sunny weather, Peak congestion period, Commuting travel, Medium-distance (3–10 km)
3	Sunny weather, Peak congestion period, Commuting travel, Long-distance (>10 km)
4	Sunny weather, Peak congestion period, Other travel, Short-distance (<3 km)
5	Sunny weather, Peak congestion period, Other travel, Medium-distance (3–10 km)
6	Sunny weather, Peak congestion period, Other travel, Long-distance (>10 km)
7	Sunny weather, Light traffic period, Commuting travel, Short-distance (<3 km)
8	Sunny weather, Light traffic period, Commuting travel, Medium-distance (3–10 km)
9	Sunny weather, Light traffic period, Commuting travel, Long-distance (>10 km)
10	Sunny weather, Light traffic period, Other travel, Short-distance (<3 km)
11	Sunny weather, Light traffic period, Other travel, Medium-distance (3–10 km)
12	Sunny weather, Light traffic period, Other travel, Long-distance (>10 km)
13	Bad weather, Peak congestion period, Commuting travel, Short-distance (<3 km)
14	Bad weather, Peak congestion period, Commuting travel, Medium-distance (3–10 km)
15	Bad weather, Peak congestion period, Commuting travel, Long-distance (>10 km)
16	Bad weather, Peak congestion period, Other travel, Short-distance (<3 km)
17	Bad weather, Peak congestion period, Other travel, Medium-distance (3–10 km)
18	Bad weather, Peak congestion period, Other travel, Long-distance (>10 km)
19	Bad weather, Light traffic period, Commuting travel, Short-distance (<3 km)
20	Bad weather, Light traffic period, Commuting travel, Medium-distance (3–10 km)
21	Bad weather, Light traffic period, Commuting travel, Long-distance (>10 km)
22	Bad weather, Light traffic period, Other travel, Short-distance (<3 km)
23	Bad weather, Light traffic period, Other travel, Medium-distance (3–10 km)
24	Bad weather, Light traffic period, Other travel, Long-distance (>10 km)

**Figure 1.** The number of respondents using bike-sharing in a week.

4. Analytical Method

The mixed logit model is a highly flexible model that can be applied to any random utility model. As the influencing factors of this study are not independent of each other and violate the assumption of the Independence from Irrelevant Alternative (IIA), the standard logit model is not appropriate in this study. Compared with the standard logit model, the utility function of the mixed logit model adds an error term that allows for correlation between the choices, which solves the problem of IIA. In addition, it presents the variables' coefficient value in a substitution pattern, which allows for various scopes in analyzing and applying heterogeneity in each respondent. Therefore, the analytical method in this study can be determined as mixed logit model.

The random utility equation of the mixed logit model is shown in Equation (1):

$$U_{ni} = V_{ni}\beta + \varepsilon_{ni} + \xi_{ni} \quad (1)$$

where V_{ni} is the deterministic part in the utility function of the individual n selecting the travel mode i ; ε_{ni} is the random term, and ξ_{ni} is the error term. The error terms can be distributed in the form of normal distribution, lognormal distribution, uniform distribution, etc.

β is the difference in preferences; $f(\beta|\theta)$ is the density function under the overall parameter θ . If there is no difference in preferences, that is, in the condition that the fixed condition of β is unchanged, the probability of travel mode selection is:

$$L_{ni}(\beta) = \frac{e^{V_{ni}(\beta)}}{\sum_{j=1}^I e^{V_{nj}(\beta)}}. \quad (2)$$

In the mixed logit model, β is randomly changed. Therefore, it is necessary to multiply the distribution of β on this basis to obtain the conditional selection probability of the behavior subject in the presence of random preference differences. The final form of the mixed logit model in the presence of random preference differences is as follows:

$$P_{ni} = \int L_{ni}(\beta) f(\beta|\theta) d\beta. \quad (3)$$

The selection probability of the mixed logit model can be regarded as the weighted average of the selection probabilities of the multidimensional logit model, and the weight is determined by $f(\beta|\theta)$. The distribution form of $f(\beta|\theta)$ is usually a normal distribution, a lognormal distribution, or a uniform distribution, etc., and can be selected according to actual conditions. The form of a probability function of a mixed logit model can take different distribution forms, resulting in the model probability function being non-closed. In addition, the density function is described by a certain parameter θ , such as a normal distribution through the mean μ and standard deviation σ .

SAS 9.4 was used to solve models. The fitness index was used to describe the degree of matching between the theoretical results and actual results of the model. Indicators including the McFadden (1974) likelihood index, Likelihood ratio R, Aldrich–Nelson, and Estrella are expressed as:

$$R_M^2 = 1 - [\ln L / (\ln L_0)] \quad (4)$$

$$\text{Likelihood ratio R} = \log L - \log L_0 \quad (5)$$

$$\text{Aldrich–Nelson} = R / (R + N) \quad (6)$$

$$\text{Estrella} = 1 - [(\ln L - K) / \ln L_0] \quad (7)$$

where L and L_0 are the maximum log likelihood function values in the model containing all variables and containing only the intercept, respectively. The values of the McFadden likelihood index, Aldrich–Nelson, and Estrella are between (0, 1). The closer the value is to 1, the better the model fits.

5. Results and Discussion

5.1. The Effect of Individual Attributes on Travel Characteristics

The first model describes the impact of individual attributes on travel characteristics (travel time and travel expense). The log-likelihood values of the two models are -7165 and -7915 , which indicates that the algorithm converges; the goodness of fit of the models is shown in Table 5, where the Estrella values are 0.552 and 0.4425, the Aldrich–Nelson values are 0.4021 and 0.3391, and the McFadden LRI values are 0.3061 and 0.2335. These values are greater than 0.2, which indicates that the models have a good fitting effect.

Table 5. The goodness of fit indicator of the individual attribute–travel characteristic model.

Measure	The Individual Attribute–Travel Time Model	The Individual Attribute–Travel Expense Model
Likelihood ratio (R)	6322.9	4823
Aldrich–Nelson	0.4021	0.3391
Estrella	0.552	0.4425
McFadden LRI	0.3061	0.2335

Reference to the travel time of >60 min(3) and the travel expense of <¥1(1) results of the model are shown in Table 6, Figures 2 and 3. The independent variables in the model include binary variables (gender and whether they own cars), continuous variables (age and personal monthly income), and multi-categorical variables (education and occupation).

Table 6. The individual attribute–travel characteristic model estimation results.

Variable	Value	The Individual Attribute–Travel Time Model				The Individual Attribute–Travel Expense Model			
		0–30 min (1)		30–60 min (2)		¥1–¥4 (2)		>¥4 (3)	
		E	P	E	P	E	P	E	P
Constant term		6.873	0.048 *	−11.3874	0.043 *	6.065	0.017 *		
gender	man(M)	1.910	0.042 *			−2.53	0.024 *		
	man(S)			11.99	0.047 *	−1.82	0.003**		
age	M			6.408	0.049 *	4.695	0.024 *		
	S					−3.83	0.011 *		
education ("Master/above" as a reference)	high school/former(M)	6.952	0.042 *	10.76	0.037 *	−6.042	0.013 *		
	undergraduate/college(M)	2.885	0.047 *	8.479	0.038 *	−2.67	0.017 *	−26.76	0.016 *
	undergraduate/college(S)					5.201	0.029 *	26.319	0.009 **
occupation ("other" as a reference)	student(M)	42.62	0.0499 *	−54.70	0.049 *	−47.19	0.037 *	−3.17	0.018 *
	student(S)					−76.82	0.039 *	−2.536	0.037 *
	institution staff(M)			−6.12	0.046 *	−3.59	0.031 *		
	institution staff(S)							−6.93	0.009 **
	business employee(M)	−6.76	0.048 *			2.193	0.028 *		
car ownership	no(M)							−1.688	0.007 **

Note: We used >60 min(3) and <¥1(1) as references; significance symbols: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Insignificant variables have been culled from this list. E stands for parameter estimate, M stands for mean, and S stands for standard deviation.

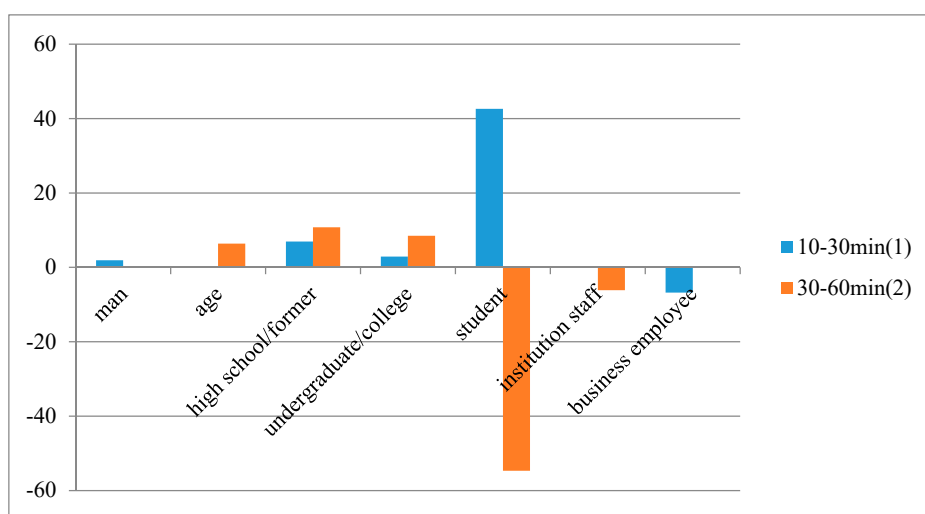


Figure 2. The parameter estimates of the individual attribute–travel time model.

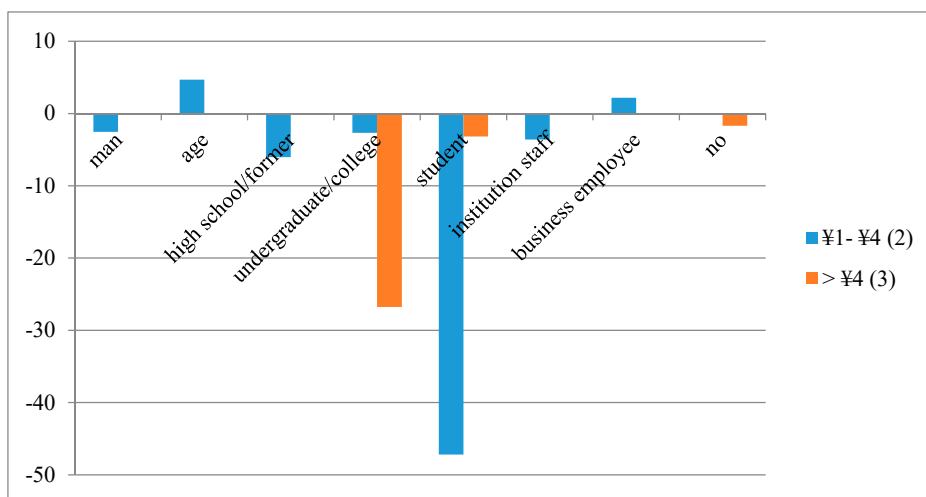


Figure 3. The parameter estimates of the individual attribute–travel expense model.

The survey of travel characteristics is based on the use of bike-sharing-related travel modes. Taking >60 min(3) and $<¥1$ (1) as references, 0–30 min and ¥1–¥4 have higher constant estimates of 6.873 and 6.065, indicating that travelers prefer to travel in short trips and with low expenses. Among the travel expenses, $<¥1$ corresponds to “only use bike-sharing,” ¥1–¥4 and $>¥4$ correspond to “use bike-sharing and other public transportation,” which indicates that travelers tend to choose short-distance travel combined with bicycle and public transportation when they choose bike-sharing.

It can be found from Table 6 that women have a positive significant influence on the choice of 0–30 min and a negative significant influence on the choice of ¥1–¥4. Women are more willing to use bike-sharing for shorter distances (0–30 min) as compared with the option of >60 min. Compared with $<¥1$, women are not willing to choose a travel mode with a fee of ¥1–¥4. Mosquera et al. [37] proposed that cycling might still not be a feasible option for a significant proportion of travelers, particularly for women. The findings of this study, however, are different. While women choose bike-sharing, they tend to shift to other public transportation after a short-distance bike-sharing ride. A higher age is positively associated with a traveler’s choice of 30–60 min with an estimated value of 6.408, which provides the best statistical fit for the normal distribution of the average value of 4.695 and the standard value of -3.83 to choose ¥1–¥4. We found that the increase in age is associated with travelers who pay more attention to the economic benefits in long-distance travel, and choose to combine bike-sharing with public transport.

The “high school/before” and “undergraduate/college” education levels have a positive significant influence on the travel time within one hour and have a negative significant impact on the travel expenses of ¥1–¥4. “Undergraduate/college” has a significant negative impact on the selection of $>¥4$ with an estimated value of -26.76 . Students have a positive significant impact on the selection of 0–30 min with an estimated value of 42.62, a significant negative impact on the selection of 30–60 min with an estimated value of -54.70 , and a significant negative impact on travel costs over ¥1. The relative probability that the institutional staff choose 30–60 min and ¥1–¥4 is relatively lower. The relative probability of the employees choosing 0–30 min is lower, and selecting ¥1–¥4 is higher. The travel time and travel expenses of the “high school/before” and “undergraduate/college” qualifications are generally less, as the “high school/before” academics are mostly middle school students who are attending school, and their general transportation is by parents or by using public transportation. In addition, school regulations on mobile phone time and safety factors limited their travel time by bike-sharing.

Some of the “undergraduate/college” qualifications overlap with the “student” occupations. The travel range of such travelers is mostly concentrated on campus, and the time and cost of using bike-sharing-related travel modes are relatively low. For those who have already worked, the travel

time and cost of using bike-sharing is increased due to the distance between the workplace and the place of residence. For those who do not have a car, the relative probability of choosing ¥4/¥1 is lower than car owners. Most of these people are commuters with low to medium income and tend to use a combination of bike-sharing and public transportation for medium or long-distance travel.

5.2. The Effects of Various Factors on Bike-Sharing Usage Frequency

A mixed logit model was used to explore the influence of various factors on bike-sharing usage frequency. The log-likelihood value is -9432 , which indicates that the algorithm converges. As shown in Table 7, the Estrella value, Aldrich–Nelson value, and McFadden LRI value are 0.5919, 0.4337, and 0.2762, respectively. It was found that the model has a good fitting effect.

Table 7. The goodness of fit indicator of the various-factor bike-sharing usage frequency model.

Measure	Value
Likelihood ratio (R)	7198.9
Aldrich–Nelson	0.4337
Estrella	0.5919
McFadden LRI	0.2762

Taking 0 time(1) as a reference in the model, the independent variables include binary variables (gender, whether they own a car, transfer distance, and travel preference), continuous variables (age, personal monthly income, travel time, and travel expense), and multi-categorical variables (education and occupation). The results are shown in Table 8 and Figure 4.

Table 8. The various-factor bike-sharing usage frequency model estimation results.

Variable	Value	1–2 Times (2)		3–5 Times (3)		>6 Times (4)		
		E	P	E	P	E	P	
Constant term		8.4205	0.0003 ***			−33.37	0.0002 ***	
age	M	−1.76	0.04 *	−9.00	0.0004 ***			
education('Master/above' as a reference)	high school/former(M)	1.48	0.0005 ***			−25.16	0.0008 ***	
	high school/former (S)							
	undergraduate/ college (M)	10.936	0.009**			−5.52	0.0004 ***	
	undergraduate/ college (S)	11.21	0.0003 ***					
occupation('other' as a reference)	student (M)	−3.18	0.0002 ***	−31.34	0.0001 ***	6.38	0.04 *	
	student (S)	−0.75	0.0006 ***	−43.52	0.0001 ***			
	institution staff(M)					8.03	0.03 *	
	institution staff(S)					8.70	0.04 *	
	business employee (M)					11.48	0.002 **	
	business employee (S)					11.28	0.0003 ***	
monthly income	M	−6.9	0.0005 ***			−5.24	0.0005 ***	
	S	−22.66	0.0001 ***	−7.34	0.0006 ***	−13.06	0.0003 ***	
car ownership	no (M)	−1.25	0.0002 ***	−4.46	0.0002 ***	−5.24	0.0005 ***	
	S	−2.473	0.0002 ***	4.933	0.0002 ***	24.894	0.0002 ***	
distance between site and destination('1500m' as a reference)	500m(M)			−0.824	0.009 **	5.062	0.0001 ***	
	500m(S)							
	800m(M)	−1.48	0.0004 ***	5.18	0.0004 ***			
	1000m(M)	2.096	0.0002 ***	8.190	0.0001 ***	2.90	0.0008 ***	
travel time	M			2.086	0.0007 ***	−3.38	0.0003 ***	
travel preference	time saving	yes (M)	1.47	0.0006 ***	9.53	0.0003 ***		
		yes (M)	0.577	0.006 **	2.14	0.0003 ***	1.763	0.0002 ***
	economic	yes (S)			2.79	0.0002 ***	−0.871	0.002 **
	comfort	yes (M)			−2.17	0.004 **	−1.56	0.0003 ***
	environmental friendly	yes (M)	0.614	0.019 *	9.17	0.0004 ***	2.054	0.0003 ***
	safety	yes (M)	−1.23	0.0009 ***	−5.47	0.0001 ***	−2.73	0.0007 ***

Note: We used 0 time(1) as a reference; significance symbols: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Insignificant variables were culled from this list. E stands for parameter estimate, M stands for mean, and S stands for standard deviation.

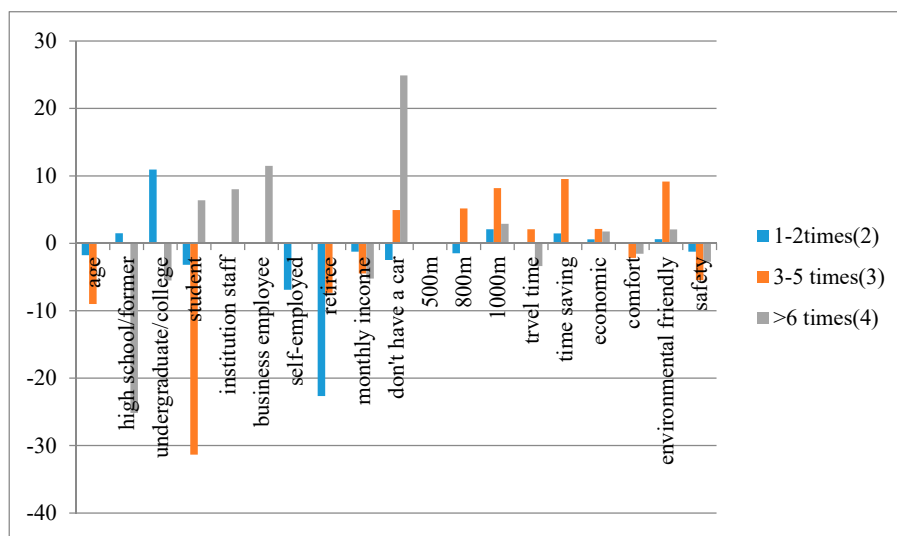


Figure 4. The parameter estimates of the various-factor bike-sharing usage frequency model.

Taking 0 times (1) as the reference, 1–2 times (2) and >6 times (4) have constant estimates of 8.4205 and –33.37, indicating that most travelers use bike-sharing 1–2 times in a week, and a small number of people use bike-sharing more than six times in a week.

Table 8 shows the relative probability reduction of choosing 1–2 times (2)/0 times (1) and 3–5 times (3)/0 times (1) with the increase of age. The use of bike-sharing requires a traveler’s physical fitness and access to mobile phones, thus those with older ages are less likely to use bike-sharing. This is consistent with the reality.

Taking the master’s degree as a reference, “high school/before” and “undergraduate/college” have a significant positive influence on the choice of 1–2 times (2), and have a significant negative impact on the selection of >6 times (4), indicating that people who have higher education will often use bike-sharing-related travel modes. Regarding the level of education, studies show that people with higher education travel more using public transportation (especially leisure travel) [38,39]. Bike-sharing as an emerging product under the Internet+ model advocates a healthy and environmentally friendly concept of life, which is consistent with public transportation, thus bike-sharing is more likely to be accepted by people with higher education levels, and such people have a higher tendency to shift.

Taking other occupations as the reference, students have a negative significant impact on the choice of 1–2 times (2) and 3–5 times (3), and have a positive significant impact on the choice of >6 times (4). Being an institutional staff or a business employee has a positive significant impact on the choice of >6 times (4), and self-employed persons and retirees have a negative significant influence on the choice of 1–2 times (2) and 3–5 times (3). It was found that students, especially college students, travel mainly by bike-sharing. University campuses become hot-spots for bike-sharing use, while enterprises and employees tend to use bike-sharing frequently. Such travelers have a fixed commuter mode of bike-sharing and public transportation. The frequency of self-employed persons and retirees using bike-sharing is generally low, as self-employed people have higher flexibility in travel modes, higher incomes, and travel is based more on private transportation. As retirees are generally older, in line with the above analysis of age variables, they use bike-sharing at a lower frequency.

Compared with 0 (1), the increase of personal monthly income has a negative significant impact on the choice of the other three frequencies for the travelers: –1.25, –4.46, and –5.44. We found that the higher the personal monthly income, the less likely the traveler will be to choose bike-sharing, which is consistent with Habib’s (2014) study. Owning a car has a very positive significant impact on the choice of >6 times (4). These travelers are low-and middle-income commuters, and the economic benefits and convenience of bike-sharing attract such travelers. In the transfer distance, the relative probability of 800m for choosing 3–5 times (3) is increased, and 1000m has a high positive significant impact on

the selection of each type of frequency, indicating that the traveler tends to choose a bike-sharing ride when the transfer distance is 800m or 1000m, which reflects the advantage of bike-sharing to solve the “last mile” problem. Bike-sharing becomes a bridge between the destination and the bus station with a short distance, reflecting its advantage as a new type of travel that can achieve point-to-point travel, which is not available through public transportation or the subway.

The increase in travel time has a positive significant impact on the selection of 3–5 times (3), and has a negative significant impact on the selection of >6 times (4), indicating that travelers tend to use bike-sharing in cases of short-distance travel. In the travel characteristics, travelers who have “saving time,” “environmental protection,” and “economic” awareness tend to use bike-sharing frequently. Travelers with “comfort” and “safety” awareness tend not to use bike-sharing. This also reflects the characteristics of bike-sharing, which include the advantages of time-saving economy, health, and environmental protection and the disadvantages of low comfort and weak safety.

5.3. Analysis of the Mixed Scenario–Transfer Willingness Model

A mixed logit model was used to study the degree of shifting willingness to choose bike-sharing-related travel modes in different situations. The frequency of willingness for each scenario is shown in Table 9. The log-likelihood value is -16362 , which indicates that the algorithm converges. The goodness of fit of the model is shown in Table 10, where the Estrella value, Aldrich–Nelson value, and McFadden LRI value are 0.3844, 0.3421, and 0.3987, respectively.

Table 9. The frequency of willingness for each scenario.

Hypothetical Scenarios	Degree of Willingness				
	Completely Unwilling(1)	Not Willing(2)	Generally Willing(3)	More Willing(4)	Very Willing(5)
1	80	125	273	229	938
2	129	252	419	436	409
3	415	293	314	262	361
4	79	137	275	285	867
5	153	220	497	346	429
6	407	236	419	189	394
7	69	114	327	391	744
8	182	181	481	394	407
9	426	241	413	257	308
10	106	84	344	370	741
11	209	205	423	371	437
12	465	215	363	279	323
13	649	192	343	183	278
14	709	212	307	198	219
15	836	211	263	148	187
16	694	236	291	183	241
17	765	229	287	187	177
18	847	200	232	168	198
19	740	244	256	195	210
20	770	238	326	146	165
21	832	218	243	167	186
22	735	259	282	183	186
23	807	213	304	150	171
24	882	196	233	153	182

Table 10. The goodness of fit indicator of the mixed scenario–shifting willingness model.

Measure	Value
Likelihood ratio (R)	3585.5
Aldrich–Nelson	0.3412
Estrella	0.3844
McFadden LRI	0.3987

Taking unwilling(1) as a reference, the results are shown in Table 10 and Figure 5. The model independent variables include binary variables (weather, travel time, and travel purpose) and continuous variables (travel distance). As the number of valid questionnaires was 1645, and the SP survey section of each questionnaire contained 24 scenario questions, the final sample size was 39,480.

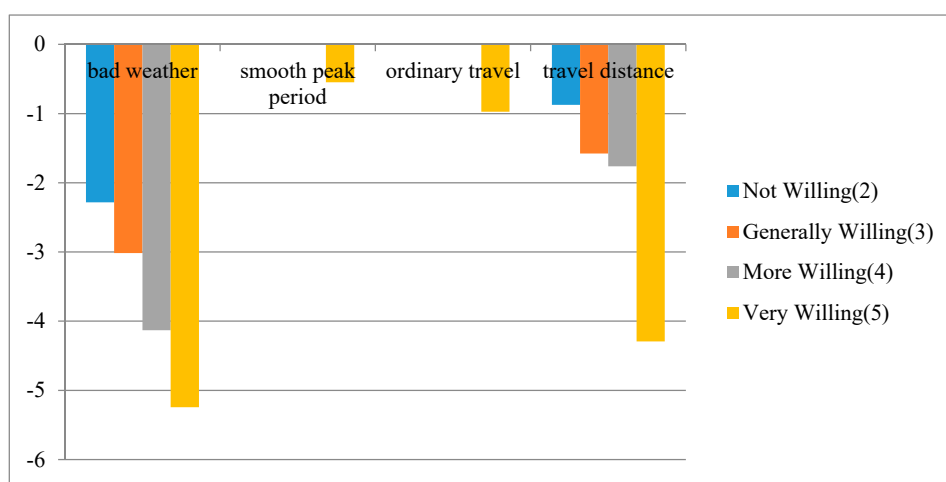


Figure 5. The parameter estimate of the mixed scenario–shifting willingness model.

In Table 11, travel distance is a random coefficient, and so for weather, travel time, and travel purpose, the standard deviation estimates are not significantly different from 0. Hence, the coefficient is a fixed value, indicating whether these variables are included, regardless of whether these variables include the choice to shift to the bike-sharing willingness in the mixed scenario. Their values are fixed, and the probability prediction values are shown in Table 11.

Table 11. The mixed scenario–shifting willingness model estimation results.

Variable	Value	Not Willing(2)		Generally Willing(3)		More Willing(4)		Very Willing(5)	
		E	P	E	P	E	P	E	P
Constant term		0.465	0.001 **	1.275	0.0004 ***	1.432	0.0001 ***	2.781	0.0005 ***
weather	bad (M)	−2.282	0.0002 ***	−3.017	0.0003 ***	−4.132	0.0001 ***	−5.243	0.0002 ***
travel period	light traffic (M)							−0.548	0.001 **
travel purpose	ordinary (M)							−0.973	0.040*
travel	M	−0.874	0.001 **	−1.576	0.0003 ***	−1.761	0.0002 ***	−4.294	0.0005 ***
distance	S	1.078	0.001 **	−1.597	0.0003 ***	1.840	0.0004 ***	−4.746	0.0001 ***

Note: We used completely unwilling(1) as a reference; significance symbols: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Insignificant variables were culled from this list. E stands for parameter estimate, M stands for mean, and S stands for standard deviation.

The traveler’s choice of the “very willing” constant estimate (2.78) is higher than the other options, which indicates that the traveler has a positive attitude towards the shift to bike-sharing-related travel modes. As shown in Table 10, the weather and travel distance have a significant impact on each

traveler's willingness to shift, and these factors have a significant influence on the "very willing" transfer intention, including travel time and travel purpose.

The travel distance has significant mean and standard deviation, which provide the best statistical fit for the normal distribution of the average value of -4.294 and the standard value of -4.746 for residents' willingness to choose "very willing." Compared with the parameter estimates, the travel distance has the greatest impact on the "very willing" attitude, as the tolerable distance of bicycle travel is less than 10 km. As the travel distance increases, the cyclists' comfort decreases. Therefore, the few travelers who travel farther tend to choose bike-sharing. This is consistent with the effect of the "distance between site and destination" mentioned above on the bike-sharing usage frequency. That is, bike-sharing is only suitable for short-distance travel.

Severe weather has a negative impact on any willingness. The parameter with the "very willing" attitude is the largest, which indicates that if the weather changes from sunny to bad, the willingness to shift to the bike-sharing-related travel modes will be greatly reduced. This embodies the fact that bike-sharing is greatly affected by the natural environment, including the weather.

Relative to the peak hour, the relative probability that travelers choose "very willing (5)/completely unwilling (1)" during the light traffic period is slightly reduced. Relative to commuting, the relative probability of choosing "very willing (5)/completely unwilling (1)" on traveling leisurely is also slightly lower. This indicates that for travel during the peak period and for commuting, travelers are more willing to use bike-sharing. This is also in line with the actual scenario, as the travel combination of bike-sharing and public transportation is less affected by external traffic, which can ensure punctuality and accessibility, and can meet modern society's pursuit of a natural and healthy green lifestyle.

6. Conclusions and Future Work

This study explored the impact of bike-sharing on the transfer of residents' travel modes by travel survey data in Nanjing, China. Taking the bike-sharing plus public transportation travel chain as the research object, the mixed logit model was used to study the influence of individual attributes, the built environment, and travel characteristics on the frequency of using bike-sharing-related travel modes, the degree of willingness to shift to bike-sharing-related travel modes under mixed scenarios, and the analysis of the significant influencing factors. The conclusions are as follows:

1. Travelers who tend to choose short-distance and low-cost travel by public transportation, tend to shift to bike-sharing for travel of about 1 km, which reflects the advantages of combining bike-sharing and other public transport modes to achieve point-to-point travel.
2. Older and higher-income travelers use bike-sharing with a lower frequency and have a lower tendency to shift. Students, enterprise employees, people without a car, individuals with low monthly income, and highly educated travelers (undergraduate/above) prefer to travel by bike-sharing. As this type of travel mode has health benefits and low travel costs, it is more popular among young people with low to middle income, who have a higher tendency to shift. Students with "college/undergraduate" degrees use bike-sharing with high frequency and for short durations, which indicates that college students use bike-sharing as the main means of transportation on campus. Currently, many universities in China have launched exclusive bike-sharing services within their campuses, which is consistent with the findings of this study, as shown in Figure 6. Also, travelers who focus on the "time saving," "environmental protection," and "economic" characteristics tend to use bike-sharing on a regular basis.
3. In the mixed scenario-transfer willingness model, compared with the four influencing factors, the impact of riding distance on riders' comfort is significantly obvious, and the impact of the weather on riding safety is also very distinct. Hence, the willingness of travelers to shift to bike-sharing-related travel modes is greatly affected by the weather and travel distance. Travelers are more willing to use bike-sharing-related travel modes when the weather is clear and the distance is short. Different travel periods and travel purposes have a weak influence on the willingness to transfer. Compared with the light traffic travel times and other travel, travelers'

transfer attitudes tend to be “very willing” for peak travel times and for commute trips, as the combination of bike-sharing plus public transportation is less affected by external traffic, and punctuality and accessibility can be guaranteed.

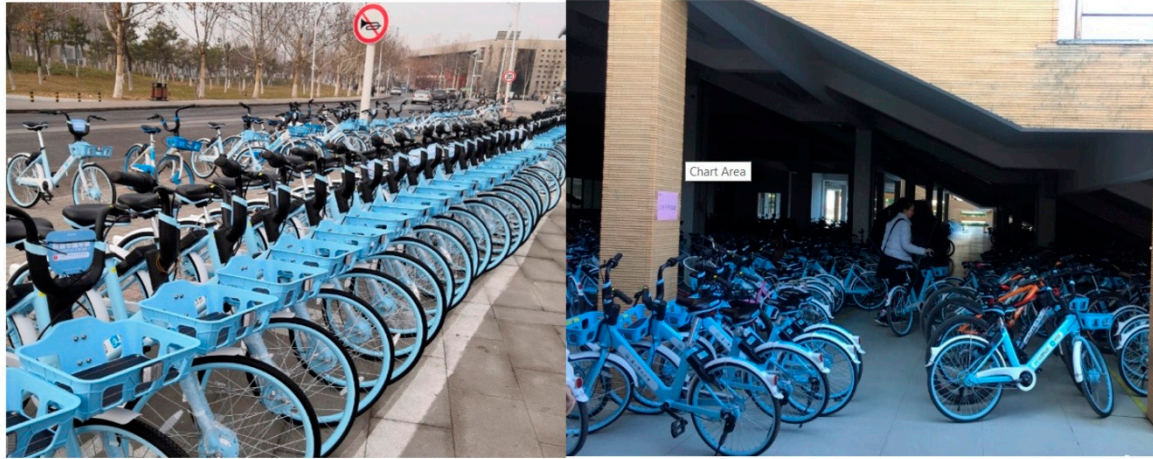


Figure 6. Bike-sharing exclusive to a campus.

Previous studies considered only the influencing factors of bike-sharing trips [2], the safety of bike-sharing trips [40], or the factors that affect the frequency of bike-sharing [41]. In this article, the bike-sharing and public transportation travel chain was set as a travel mode. In addition, we explored the influence of factors such as personal attributes and the built environment on the choice of bike-sharing-related travel modes, as well as the degree of willingness of residents to transfer to bike-sharing-related travel modes, by constructing a mixed scenario set composed of multiple factors. This is an entry point that has not appeared in previous researches. A mixed logit model was used for analysis, which solved the IIA characteristics of other discrete models and satisfied the heterogeneity between individuals [36,42].

There are still some problems with the existing management and service of bike-sharing. For example, there may be problems where users cannot find vehicles when they need them, and some places have bike-sharing that are stranded. The influencing factors of travelers' shifts to bike-sharing are unknown, so this study selected individual attributes, travel characteristics, built environment, and hypothetical scenarios to explore their impacts on the shift to bike-sharing-related travel modes. Overall, the conclusions have reference significance for improving the management and service capacity of bike-sharing in Nanjing and other cities similar to Nanjing. According to different types of travelers' shift tendencies, bike-sharing operators can target the delivery of bike-sharing at different time points in different places (e.g., school campuses, public transportation sites, residential areas, and companies), so as to achieve the most effective use of their resources. The operating company scientifically deploys the number and times of shared bicycles for buses, subway stations, and surrounding dwellings to ensure the continuity of bike-sharing services between stations and dwellings, and effectively promotes the travel chain combining bike-sharing and public transport. In addition, according to the nature of land use and population composition of the area, the allocation of the number of shared bicycles can be guided. The result is a high volume of bicycles for students, enterprise employees, travelers without a car who are keen on bike-sharing. At the same time, bike-sharing operators can establish a more complete workflow and system for the placement, parking, operation, and maintenance of bicycles. According to the degree of traveler willingness to use bicycles in different scenarios, enterprises also need to continuously optimize their services and provide some humanized services such as safety reminders, navigation guides, weather forecasts, etc. The government and regulators should introduce relevant management rules and regulate the quality of the bike-sharing industry. Operating companies

can promote the use of bike-sharing by online and offline services, improve service levels, and cooperate with government departments to publicize and guide city cycling.

There are two limitations on this study. First, the sample size could be larger. Although the collected data samples cover the travel groups with different attributes and the expected conclusions are obtained, the sample size is generally small, and follow-up can continue to increase the data samples to further enhance the credibility of the conclusions. Secondly, the mixed scenarios have few impact factors. This study considered the four influencing factors of weather, travel time, travel distance, and travel purpose when setting the scenario, which is not entirely comprehensive. More factors should be considered in future studies, including travel cost-related variables, to achieve more specific mixed scenarios. In addition, future work can add the difference between the travel modes before and after the shift, and analyze the transfer sources of travelers who use bike-sharing, to obtain the specific shift trend of the travelers' shifts to the bike-sharing-related travel mode in complex scenarios.

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