

Article

College Students' Shared Bicycle Use Behavior Based on the NL Model and Factor Analysis

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Abstract: The rise and rapid development of bicycle sharing brings great convenience to residents' travel and transfer, and also has a profound impact on the travel structure of cities. As college students make up a major share of shared bicycle users, it is necessary to analyze the factors that influence their travel mode and riding frequency choice and to explore how these factors affect their riding behavior. To analyze the bicycle riding characteristics of college students, this paper processes many factors with unknown correlations by using a factor analysis method based on revealed preference (RP) questionnaire data. Then, taking the significant common factors as explanatory variables, a two-layer nested logit (NL) model combining riding frequency and travel mode is established to study college students' riding behavior. The results suggest that the comprehensive hit rate of the upper and lower levels of the model (riding frequency and travel mode) are, respectively, 76.8% and 83.7%, and the two-layer NL model is applicable. It is also shown that environmental factors ("cheap," "mixed traffic," "signal lights at intersection," and so on) have a significant impact on the choice of travel mode and riding frequency. Also, improving the level of bicycle service can increase the shift from walking to riding. Such findings are meaningful for policy-makers, planners, and others in formulating operational management strategies and policies.

Keywords: college students; bicycle sharing; nested logit model; factor analysis method; sensitivity analysis

1. Introduction

Due to urban traffic congestion, environmental pollution, traffic accidents, and other issues, many scholars and policy-makers are paying attention to more sustainable travel modes. As an environmentally friendly, convenient, and low-cost travel mode, bicycle sharing helps to adjust the unbalanced traffic structure and provide an alternative travel mode for short trips, commutes, and transfer trips. Moreover, it can guide multimodal travel and provide a low-carbon solution for the "last mile" problem. In the past 50 years, bicycle sharing systems have experienced three mature stages: The white bikes system [1], the coin-deposit system [2], and the information technology (IT)-based system [3]. The latest bicycle sharing system allows users to use shared bicycles at dockless points. Borrowing and returning bikes is on a self-service basis, which greatly improves the convenience of access and return [4,5]. China's Mobike and ofo bicycle sharing systems are two typical representatives. By the end of 2017, China had developed more than 300 service systems, with more than 10 million shared bicycles, more than 100 million registered users, and more than 1 billion passengers, shaping the world's largest bicycle sharing market [6]. Among shared bicycle users, the 20-to-30-year-old age group accounted for 50.3% [7], and college students are the main component of this age group. Generally, college students have a strong ability to accept new things, a high degree of education,

and limited daily expenditures; and they usually have a strong sense of safety and environmental protection. It is necessary to analyze their travel choice behavior under these influencing factors.

Relevant research on shared bicycles and traditional bicycles has been carried out in terms of riding frequency, riding influence factors, and travel mode selection. Public bicycles and electric bicycles are chosen as research objects to analyze the impacts of the physical environment [8], season [9], temperature [10], and traffic facilities [11]. Campbell et al. explored riders' individual factors (including gender, age, education level, etc.) influencing the riding choice of Beijing residents, and concluded that female riders tend to choose public bicycles, older riders are more inclined to choose electric bicycles, and riders with a higher education level tend to choose public bicycles [12]. Dickinson and Mohanty et al. found that the number of nonmotorized lanes is proportional to bicycle usage, and the width of the sidewalk, intersection status, and land use around the site are important factors affecting nonmotorized transportation [13,14]. Moudon et al. emphasized that perceived environmental factors represented by road environment safety, traffic congestion, group effect, etc., have different degrees of impact on the choice of riding [15].

The discrete selection model is the most extensive and mature analysis method to study travel mode choice and riding frequency. Through combined travel mode–trip chain type (nested logit) [16], place of residence–travel mode–departure time (cross-nested logit) [17], and travel time–travel mode (mixed logit) [18] models, researchers have analyzed travel behaviors. Tang et al. established a binary logit (BL) model to analyze the main factors affecting riding frequency in Shanghai [6]. Faghih-Imani et al. explored the impact of bicycle infrastructure attributes and land use characteristics on shared bicycle riding frequency with a linear mixed logit model [19].

Some scholars have studied the travel preferences of specific travel groups. Hess and Mitra et al. modeled the travel structure of commuter groups and student groups, respectively, and found that parking fees and transfer time are important factors affecting commuter groups, while the distance between home and school, and the built environment around their place of residence has a significant impact on students' choice of travel mode [20,21]. Guo and Davidov's research on travel psychology and travel habits showed that residents' satisfaction with a bicycle operation system is an important factor. Travel habits have a greater impact on the choice of riding than the built environment [22,23].

On the whole, there are many individual studies on riding characteristics or factors affecting riding. However, there is still no comprehensive study of travel characteristics, influencing factors, travel modes, and frequency selection of shared bicycle users; and related research on operation optimization measures and policy formulation of shared bicycle systems is also relatively lacking. In addition, the latest statistics show that college students account for a relatively high proportion of daily active users of shared bicycles. However, there is still a lack of specific research on the travel characteristics and behaviors of this user group [7]. Therefore, based on an analysis of the individual characteristics, riding habits, travel characteristics, and influencing factors of college students, this paper takes the college student group as the research object and uses a factor analysis method to process a large number of influencing factors with unknown correlations. Then, the significant common factors are selected as the model explanatory variables to establish the riding frequency–travel mode combined nested logit (NL) model. Finally, this paper proposes optimization measures and suggestions through sensitivity analysis.

2. Data and Methods

2.1. Data Acquisition and Travel Characteristics

College students are better able to accept new things and thus have become the main shared bicycle users. Usually, they have a higher level of knowledge and good travel habits, and travel more frequently, for mostly short-distance trips [24]. The area selected for this research along the South Second Ring Road in Xi'an is a center of science, education, culture, health, trade, and tourism. There are many colleges and universities within 6 km (total) on both sides of the South Second Ring Road,

where we got good representation and high data quality. Considering land use and transportation facilities, 15 universities (19 survey areas) were selected, of which Chang'an University and Xi'an Jiaotong University are each divided into three campuses.

The basic data for this paper was obtained through an RP survey conducted from 27 December 2017 to 20 January 2018. According to the number of samples allocated by each survey point, questionnaires were randomly distributed in the library, student dormitories, etc., at each survey site. In total, 600 questionnaires were distributed, and 483 valid questionnaires were collected. The content of the questionnaire included three parts: Individual characteristics, riding habits, and travel characteristics. College students' travel modes include walking; taking the bus, metro, or taxi; and riding a bicycle (including ofo, Mobike, public, and personal bicycles; ofo and Mobike are the two commonly used shared bicycle services; public bicycles need fixed parking piles). Based on the questionnaires, the travel characteristics are analyzed as follows.

2.1.1. Individual Characteristics and Riding Habits

The distribution of respondents' individual characteristics and riding habits is summarized in Tables A1 and A2 in Appendix A. In order to more intuitively reflect the travel characteristics of college students using shared bicycles, we summarize some important travel information (such as riding frequency, acceptable riding time, acceptable cycling mileage, etc.) in Figure 1.

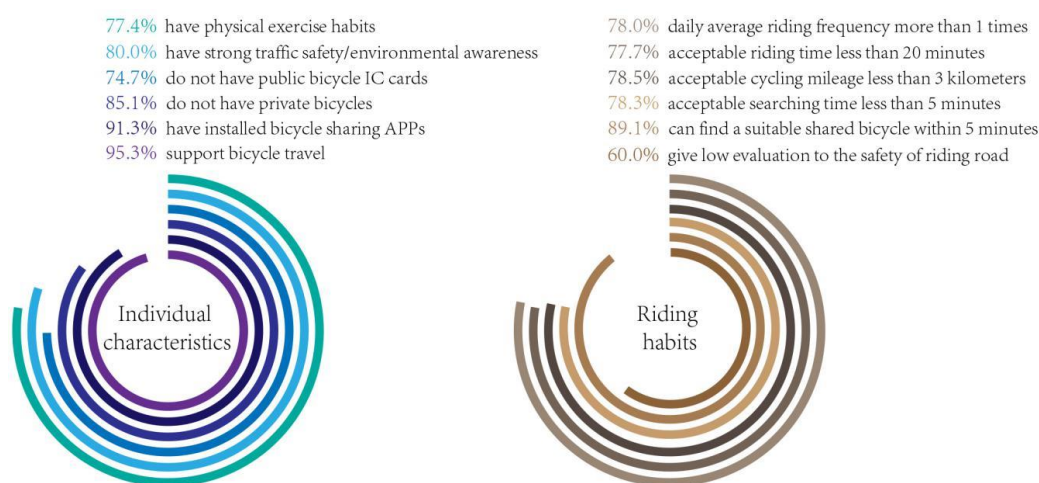


Figure 1. Individual characteristics and riding habits.

This paper establishes a 10-point Likert scale to investigate satisfaction with the riding environment, and uses very low, low, high, and very high to describe road safety for college students. Of the total respondents, 58.5% marked their satisfaction with the road riding environment below 6 points, while 24.2% marked it above 8 points; 60% of respondents rated the road safety as low or very low. Based on the above data, the respondents' basic requirements for shared bicycle travel can be roughly determined as: Easy of use and return, and that they are mainly used for short-distance travel and to meet commuting or transfer needs.

2.1.2. Trip Characteristics

As shown in Table 1, the daily travel of college students is mainly based on walking and riding a bicycle, accounting for about 48% and 41%, respectively. The public bicycle travel mode accounts for only 2%, which means that shared bicycles, represented by Mobike and ofo, occupy a large proportion (94.9%). More than 85% of travel distances were within 2 km, and travel time is within 20 minutes. This also proves that bicycle travel is mainly for short-distance commuting and transfer.

Table 1. Distribution of respondents' trip characteristics.

Survey Content	Option	Sample	Percent	Survey Content	Option	Sample	Percent
Travel mode	Walking	232	48%	Travel purpose	Attending class	135	28%
	ofo	125	26%		Returning	112	23%
	Mobike	63	13%		Shopping	72	15%
	Transit	24	5%		Entertainment	72	15%
	Subway	24	5%		Lab attendance	53	11%
	Public bicycle	10	2%		Transferring	24	5%
	Personal bicycle	0	0%		Visiting friends	15	3%
	Taxi	5	1%				
Travel distance (km)	≤0.5	59	12.2%	Travel time (min)	≤5	42	8.7%
	0.5–1	65	13.4%		5–10	156	32.3%
	1–1.5	197	41.0%		10–15	122	25.3%
	1.5–2	96	19.8%		15–20	97	20.1%
	2–4	33	6.8%		20–25	46	9.5%
	>4	33	6.8%		>25	20	4.1%

2.2. Methods

2.2.1. Nested Logit Model

The logit model is one of the commonly used methods for travel behavior analysis. It is based on random utility theory, assuming that the traveler is absolutely rational and always chooses the most effective travel plan to complete his/her trip. Travel utility can be expressed by

$$U_{jn} = V_{jn} + \varepsilon_{jn}, V_{jn} = \sum_{m=1}^M \alpha_m x_{jnm} \quad (1)$$

where V_{jn} is fixed utility, usually described as a linear function of measurable factors; ε_{jn} is random utility; X_{jnm} is the independent variable; α_m is the coefficient of independent variable x_{jnm} ; and m is the number of independent variables.

The nested logit (NL) model is different from the multinomial logit (MNL) model and binary logit (BL) model, by setting up a multiple or multilayer nest structure, which overcomes the IIA (Independence of irrelevant alternatives) characteristic of the traditional logit model to a certain extent. In the statistical analysis of survey data, we found that the riding frequency has a greater impact on the travel behavior of college students than the travel mode. In addition, we extracted 80 questionnaires for pre-modeling, then compared the goodness of fit of the riding frequency-travel mode model with the travel mode-riding frequency model. In the actual measurement, the travel mode-riding frequency model showed that the models do not converge. Therefore, referring to previous research [16,17,25], this paper takes the average daily riding frequency as the model's upper level and the travel mode as the lower level, establishing a double-layer NL model. The upper model contains three nests: Riding frequency ≤ 0.5 (Q1), riding frequency > 0.5 but ≤ 1 (Q2), and riding frequency > 1 (Q3). The lower model contains six branches: walking (Y1), public bicycles (Y2), Mobike (Y3), ofo (Y4), transit (Y5), and subway (Y6). Due to the large statistical differences in travel characteristics between the daily users of Mobike, ofo, and public bicycles, the performance, coverage, and billing standards of the three types of bicycles are also significantly different, and the user groups also have higher independence. Therefore, in this paper, three types of bicycles are used as independent travel modes for model construction. The structure of the NL model is shown in Figure 2.

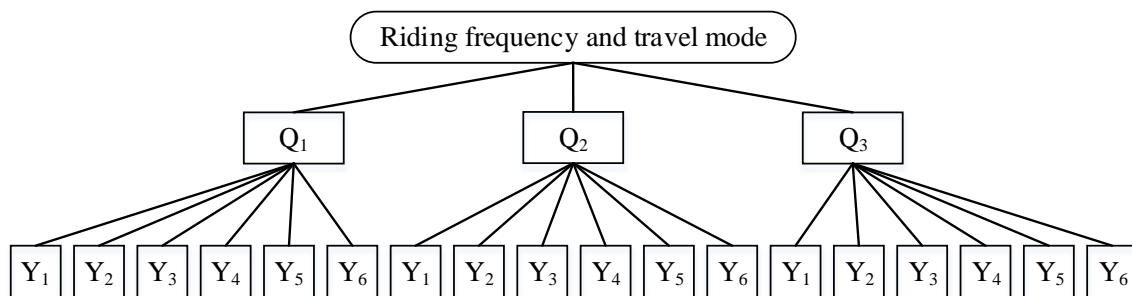


Figure 2. Riding frequency–travel mode nested logit (NL) model structure.

Taking nest Q_1 and its selection branch as an example, the probability of each branch under the established selection conditions of nest A is as follows:

$$P(i|Q_1) = \frac{\exp(V_{i|Q_1})}{\sum_{k=1}^6 \exp(V_{k|Q_1})} \quad (2)$$

where i is the branch under nest Q_1 , and $P(i|Q_1)$ is the probability of selecting branch i under the condition of selecting nest Q_1 .

The selection probability of each branch is as follows:

$$P(i) = P(i|Q_1) \times P(Q_1) \quad (3)$$

$$P(Q_1) = \frac{\exp(V_{Q_1})}{\exp(V_{Q_1}) + \exp(V_{Q_2}) + \exp(V_{Q_3})} \quad (4)$$

$$V_{Q_1} = \theta_{Q_1} \cdot X_{Q_1} + V'_{Q_1} \quad (5)$$

$$V'_{Q_1} = \frac{1}{u_{Q_1}} \ln \left[\sum_{i=1}^6 \exp(V_i) \right] \quad (6)$$

where θ is the coefficient of the independent variable of the utility function (corresponding to the nest), X is the independent variable of the utility function (corresponding to the nest), V' is the total utility value of the lower branches, u is dissimilar parameters of each nest, $1/u$ is inclusive value, and $P(i)$ is the probability of branches.

2.2.2. Factor Analysis Method

College students' travel mode choices are affected by many factors. However, the correlations between factors are not clear, and the basic data obtained are mostly in the form of 0–1 or ordered. If the NL model is directly constructed without data form transformation and correlation analysis of explanatory variables, serious multicollinearity problems might occur. In addition, it is not possible to ensure that the explanatory variables are independent of each other. Therefore, this paper first uses the factor analysis method to deal with the original influencing factors; then, the common factor is selected as the model independent variable to build the NL model.

The essence of factor analysis is the linear representation of observable variables as a number of unobservable variables. The mathematical expression for factor analysis is shown in Equation (7):

$$\Psi = \left(\Psi_1 \quad \cdots \quad \Psi_k \quad \cdots \quad \Psi_m \right)^T = A \cdot F \quad (7)$$

$$A = \begin{pmatrix} a_{11} & \cdots & a_{1j} & \cdots & a_{1n} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ a_{k1} & \cdots & a_{kj} & \cdots & a_{kn} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ a_{m1} & \cdots & a_{mj} & \cdots & a_{mn} \end{pmatrix} \quad (8)$$

$$F = (F_1 \quad \cdots \quad F_j \quad \cdots \quad F_n)^T \quad (9)$$

where Ψ is the explanatory variable of the model dependent variable, F is the common factor vector, a_{kj} is the coefficient of linear expression, m is the number of explanatory variables, and n is the number of common factors.

According to the formula, the linear function that expresses the common factor as an explanatory variable is as follows:

$$F = A^{-1} \cdot \Psi \quad (10)$$

It can then be used as the logit model branches' independent variable of utility function, as follows:

$$\text{Logistic}(i) = V_i = \theta_i \cdot F \quad (11)$$

Based on the above analysis, the process of these two methods, as used in this work, is shown in Figure 3.

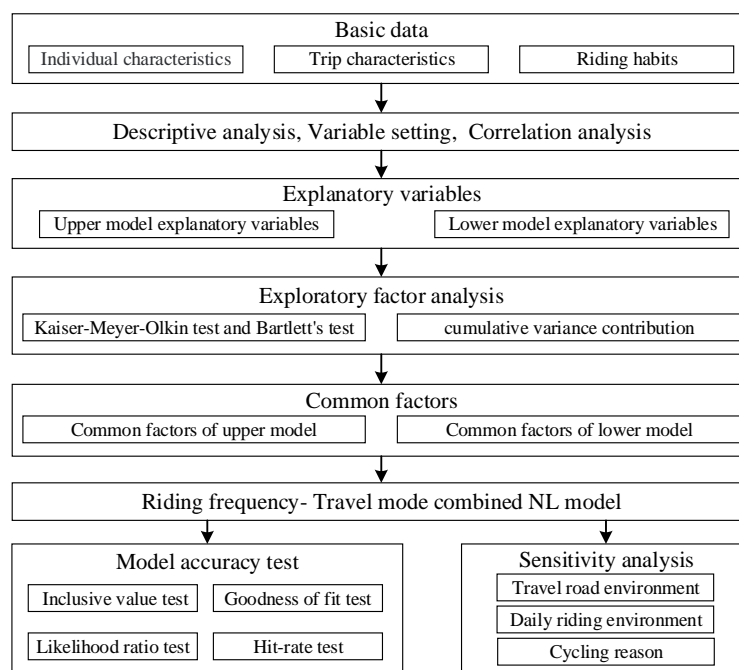


Figure 3. Analysis process.

3. Results

3.1. Setting of Upper and Lower Model Explanatory Variables

We combined the characteristics of the survey data, setting the variable types to categorical, ordered, 0–1, and continuous in SPSS software (version 20, IBM, United States), and analyzed the correlation between the model dependent variable (upper: riding frequency; lower: travel mode) and influencing factors. According to the analysis, there is a strong correlation between travel mode and 56 factors, and between riding frequency and 36 factors, as shown in Tables A3 and A4 (see Appendix B).

3.2. Exploratory Factor Analysis of Explanatory Variables

Further analysis of the Spearman coefficients of the lower and upper models (1008, 648) shows that there are 631 (about 63%) and 233 (about 37%) significant values corresponding to the Spearman coefficients less than or equal to 0.05, respectively. This indicates that the explanatory variables are highly correlated. In addition, we analyzed the explanatory variables according to their grouping, and extracted 10 groups (upper: Four groups; lower: Six groups) for the correlation test, and eight groups showed significant intervariable correlation. Taking variables Z13–Z19 belonging to “Cycling experiences” as an example, the results of correlation analysis between explanatory variables are shown in Table 2.

Table 2. Correlation analysis between influence factors (Z13–Z19).

Variables		(Z ₁₃)	(Z ₁₄)	(Z ₁₅)	(Z ₁₆)	(Z ₁₇)	(Z ₁₈)	(Z ₁₉)
Operational convenience (Z ₁₃)	Pearson	1.000	0.335	0.316	0.264	0.241	0.229	0.382
	Sig.		0.000	0.000	0.000	0.000	0.000	0.000
Searching convenience (Z ₁₄)	Pearson	0.335	1.000	0.335	0.314	0.215	0.185	0.480
	Sig.	0.000		0.000	0.000	0.000	0.001	0.000
Returning convenience (Z ₁₅)	Pearson	0.316	0.335	1.000	0.233	0.210	0.187	0.391
	Sig.	0.000	0.000		0.000	0.000	0.001	0.000
Bicycle quality scores (Z ₁₆)	Pearson	0.264	0.314	0.233	1.000	0.343	0.229	0.421
	Sig.	0.000	0.000	0.000		0.000	0.000	0.000
Deposit security scores (Z ₁₇)	Pearson	0.241	0.215	0.210	0.343	1.000	0.301	0.431
	Sig.	0.000	0.000	0.000	0.000		0.000	0.000
Riding promotion scores (Z ₁₈)	Pearson	0.229	0.185	0.187	0.229	0.301	1.000	0.270
	Sig.	0.000	0.001	0.001	0.000	0.000		0.000
Overall satisfaction scores (Z ₁₉)	Pearson	0.382	0.480	0.391	0.421	0.431	0.270	1.000
	Sig.	0.000	0.000	0.000	0.000	0.000	0.000	

To overcome the multicollinearity that occurs when the explanatory variables are highly correlated in the modeling process, this paper uses the factor analysis method to construct new variables by an organic combination of explanatory variables to make the new variables independent of each other, and better explain the model.

Kaiser–Meyer–Olkin (KMO) and Bartlett’s spherical tests were conducted on the explanatory variables of the upper and lower models to judge whether the data were suitable for factor analysis. The KMO values of the lower and upper model explanatory variables are 0.747 and 0.803, respectively, and the significant value of the Bartlett’s test of upper and lower models is 0. Therefore, the explanatory variables of the upper and lower models are suitable for factor analysis.

The initial eigenvalues and variance contributions of the explanatory variables were determined, as shown in Table 3. There are 19 common factor eigenvalues greater than 1.0 (lower model), and the cumulative variance contribution is 69.43%; there are 15 common factor eigenvalues greater than 1.0 (upper model), and the cumulative variance contribution is 68.43%. The information retention of the upper and lower layers meet the requirements, so these common factors were extracted for model construction.

Table 3. Total variance of lower/upper models.

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Eigenvalue	% of Variance	Total % Variance	Eigenvalue	% of Variance	Total % Variance	Eigenvalue	% of Variance	Total % Variance
Lower Level									
1	5.05	9.02	9.02	5.05	9.02	9.02	4.03	7.21	7.21
2	3.86	6.90	15.92	3.86	6.90	15.92	3.30	5.89	13.10
19	1.04	1.88	69.43	1.04	1.86	69.43	1.22	2.18	69.43
20	0.99	1.77	71.20						
56	0	0	100						
Upper Level									
1	3.54	9.83	9.83	3.54	9.83	9.83	2.46	6.84	6.84
2	2.35	6.54	16.38	2.35	6.54	16.38	2.36	6.55	13.40
15	1.02	2.85	68.43	1.02	2.85	68.43	1.25	3.47	68.43
16	0.95	2.64	71.07						
36	0.78	2.17	80.60						

NOTE: Lower level components 1–56 are lower layer influencing factors (see Table A3 in Appendix B); upper level components 1–36 are upper layer influencing factors (see Table A4 in Appendix B).

3.3. Common Factor Redefinition

In order to make the common factor express the original explanatory variables more clearly and in a more concentrated form, factor rotation of the common factor load-matrix using the maximum variance method was conducted. Common factors were constructed based on the linear expression of the selected highly correlated explanatory variables. Common factors are summarized in Table A5 (see Appendix B).

The common factor X_1 is taken as an example. The scores of explanatory variable factors are shown in Table 4.

Table 4. Factor scores (X_1).

Factor	Score	Factor	Score	Factor	Score	Factor	Score	Factor	Score	Factor	Score
Z ₁	0.009	Z ₁₁	0.004	Z ₂₁	-0.005	Z ₃₁	0.007	Z ₄₁	-0.001	Z ₅₁	0.007
Z ₂	-0.009	Z ₁₂	-0.008	Z ₂₂	-0.003	Z ₃₂	-0.008	Z ₄₂	-0.001	Z ₅₂	0.005
Z ₃	0.005	Z ₁₃	0.207	Z ₂₃	-0.007	Z ₃₃	0.008	Z ₄₃	0.008	Z ₅₃	-0.009
Z ₄	-0.005	Z ₁₄	0.201	Z ₂₄	-0.005	Z ₃₄	-0.002	Z ₄₄	0.006	Z ₅₄	0.002
Z ₅	-0.003	Z ₁₅	0.207	Z ₂₅	-0.004	Z ₃₅	-0.003	Z ₄₅	0.004	Z ₅₅	0.002
Z ₆	-0.004	Z ₁₆	0.160	Z ₂₆	0.000	Z ₃₆	0.009	Z ₄₆	-0.010	Z ₅₆	-0.009
Z ₇	0.004	Z ₁₇	0.173	Z ₂₇	-0.001	Z ₃₇	-0.007	Z ₄₇	-0.016		
Z ₈	-0.005	Z ₁₈	0.182	Z ₂₈	0.006	Z ₃₈	-0.006	Z ₄₈	0.008		
Z ₉	0.006	Z ₁₉	0.208	Z ₂₉	0.003	Z ₃₉	0.002	Z ₄₉	0.001		
Z ₁₀	-0.008	Z ₂₀	0.001	Z ₃₀	0.004	Z ₄₀	-0.005	Z ₅₀	0.001		

Excluding the nonsignificant factors in which the absolute value of the factor score is less than 0.005, the expression of the common factor X_1 is

$$X_1 = 0.207Z_{13} + 0.201Z_{14} + 0.207Z_{15} + 0.160Z_{16} + 0.173Z_{17} + 0.182Z_{18} + 0.208Z_{19} \quad (12)$$

where Z₁₃–Z₁₉ belong to the “Cycling experiences” variable; therefore, the common factor X_1 is named the “Cycling experiences” factor, and 19 lower and 15 upper common factors are treated in the same way. The results are summarized in Appendix B, Table A5.

3.4. Construction of NL Model Based on Common Factors

Using 19 common factors as the lower model explanatory variables and 15 common factors as the upper model explanatory variables, the riding frequency–travel mode combined NL model can be constructed.

3.4.1. Calculation Results of Lower Model

Taking the subway as the reference category and eliminating the insignificant factors (significant values are less than 0.05), the results of the calibration of the lower model are shown in Table 5.

Table 5. Calculation results of lower model.

Travel Mode	Explanatory Variables	Coefficient	Standard Error	Wald Value	df	Significance
Walking	Constant	7.521	5.574	7.282	1	0.007
	x ₁	3.061	2.567	5.687	1	0.017
	x ₂	1.586	1.609	3.884	1	0.049
	x ₃	−1.948	1.235	9.954	1	0.002
	x ₅	1.109	1.023	4.697	1	0.030
	x ₇	−2.391	1.998	5.599	1	0.018
	x ₉	−1.748	1.545	5.119	1	0.024
Public bicycle	x ₁	−1.080	2.756	5.532	1	0.019
	x ₃	0.776	1.580	8.680	1	0.003
	x ₁₂	−0.631	1.870	4.098	1	0.043
Mobike	Constant	3.420	5.575	6.020	1	0.014
	x ₁	1.445	2.569	5.065	1	0.024
	x ₃	−0.792	1.234	6.582	1	0.010
	x ₅	0.538	1.030	4.367	1	0.037
	x ₇	−1.290	2.008	6.604	1	0.010
	x ₉	−0.797	1.549	4.239	1	0.040
ofo	Constant	5.430	5.575	6.412	1	0.011
	x ₁	2.274	2.568	5.301	1	0.021
	x ₃	−1.367	1.237	8.258	1	0.004
	x ₇	−2.207	2.007	8.170	1	0.004
	x ₉	−1.270	1.547	4.558	1	0.033
Transit	x ₉	−1.150	1.537	4.365	1	0.037
	x ₁₀	−0.825	1.004	5.291	1	0.021
	x ₁₃	−1.045	1.394	4.404	1	0.036
	x ₁₄	1.145	1.526	4.415	1	0.036
	x ₁₉	−1.834	2.033	6.378	1	0.012

According to statistical theory, under the condition that the parameter degrees of freedom is 1 and the confidence level is 0.95, when the Wald value is greater than 3.841, there is a strong correlation between the independent variable and the dependent variable; when the Wald value is slightly less than 3.841, there is a weak correlation. If the Wald value is significantly less than 3.841, the dependent variable is considered to be independent of the independent variable. It can be seen from Table 5 that the Wald values of the influencing factors of the model are all greater than 3.841, and each influencing factor has an important influence on the choice of college students' travel modes. The influencing factors and mechanism of travel mode choice are as follows:

$$\left\{ \begin{array}{l} \ln \frac{P_{11}}{P_{16}} = 7.521 + 3.061x_1 + 1.586x_2 - 1.948x_3 + 1.109x_5 - 2.391x_7 - 1.748x_9 \\ \ln \frac{P_{12}}{P_{16}} = -1.08x_1 + 0.776x_3 - 0.631x_{12} \\ \ln \frac{P_{13}}{P_{16}} = 3.420 + 1.445x_1 - 0.792x_3 + 0.538x_5 - 1.29x_7 - 0.797x_9 \\ \ln \frac{P_{14}}{P_{16}} = 5.43 + 2.274x_1 - 1.367x_3 - 2.207x_7 - 1.27x_9 \\ \ln \frac{P_{15}}{P_{16}} = -1.150x_9 - 0.825x_{10} - 1.045x_{13} + 1.145x_{14} - 1.834x_{19} \\ P_{11} + P_{12} + P_{13} + P_{14} + P_{15} + P_{16} = 1 \end{array} \right. \quad (13)$$

where P_{11} , P_{12} , P_{13} , P_{14} , P_{15} , and P_{16} , respectively, are the probability of walking, public bicycle use, Mobike use, ofo use, transit, and subway use when the upper nested values have been selected.

3.4.2. Calculation Results of Upper Model

Taking riding frequency (times/day) as less than 0.5 as the reference category, the results of the calibration of the upper model are shown in Table 6.

Table 6. Calculation results of upper model.

Riding Frequency (Times/Day)	Explanatory Variables	Coefficient	Standard Error	Wald Value	df	Significance
>0.5 to ≤1	Constant	1.999	0.484	17.041	1	0.000
	w ₁	0.808	0.143	32.023	1	0.000
	w ₃	0.465	0.181	6.586	1	0.010
	w ₄	0.306	0.142	4.615	1	0.032
	w ₅	−0.504	0.130	14.957	1	0.000
	w ₆	−0.338	0.131	6.600	1	0.010
	w ₁₀	0.349	0.125	7.836	1	0.005
	w ₁₃	0.359	0.142	6.415	1	0.011
	w ₁₄	0.430	0.156	7.539	1	0.006
	w ₁₅	0.384	0.158	5.910	1	0.015
	Logsum (1/μ)	0.251	0.166	8.437	1	0.000
>1	Constant	1.691	0.538	9.889	1	0.002
	w ₁	1.038	0.168	38.159	1	0.000
	w ₂	0.575	0.161	12.726	1	0.000
	w ₃	0.762	0.196	15.178	1	0.000
	w ₄	0.433	0.161	7.284	1	0.007
	w ₅	−0.611	0.154	15.815	1	0.000
	w ₆	−0.598	0.161	13.868	1	0.000
	w ₇	0.643	0.156	16.979	1	0.000
	w ₈	0.377	0.160	5.583	1	0.018
	w ₉	0.333	0.166	4.044	1	0.044
	w ₁₀	0.689	0.164	17.746	1	0.000
	w ₁₁	0.641	0.183	12.253	1	0.000
	w ₁₃	0.406	0.161	6.361	1	0.012
	w ₁₄	0.616	0.173	12.675	1	0.000
	w ₁₅	0.652	0.175	13.925	1	0.000
	Logsum (1/μ)	0.373	0.165	6.682	1	0.001

As for the upper model, the parameter degrees of freedom is equal to 1 and the significant value is less than or equal to 0.05, and each Wald value is greater than 3.841. It shows that the factors in Table 6 have an important influence on college students’ riding frequency. The influencing factors and mechanism of riding frequency are as follows:

$$\begin{cases} \ln \frac{P_2}{P_1} = 1.999 + 0.808w_1 + 0.465w_3 + 0.306w_4 - 0.504w_5 - 0.338w_6 \\ \quad + 0.349w_{10} + 0.359w_{13} + 0.430w_{14} + 0.384w_{15} + 0.251Logsum \\ \ln \frac{P_3}{P_1} = 1.691 + 1.038w_1 + 0.575w_2 + 0.762w_3 + 0.433w_4 - 0.611w_5 - 0.598w_6 \\ \quad + 0.643w_7 + 0.377w_8 + 0.333w_9 + 0.689w_{10} + 0.641w_{11} + 0.601w_{12} \\ \quad + 0.406w_{13} + 0.616w_{14} + 0.619w_{15} + 0.373Logsum \\ P_1 + P_2 + P_3 = 1 \end{cases} \tag{14}$$

where P_1 , P_2 , and P_3 , respectively, are the probability of riding frequency less than 0.5, between 0.5 and 1, and more than 1.

Therefore, combined with the estimation results of the upper and lower parameters of the NL model, according to the basic principle of the model, the calculation formula for the selection probability of college students' travel mode is as follows:

$$P(r, k) = P_k \cdot P_{1r} \quad (15)$$

where P_k is the probability of riding frequency as grade k , and P_{1r} is the probability of travel mode r under the condition of riding frequency as grade k .

3.4.3. NL Model Accuracy Test

The model was tested from four aspects: Inclusive value, likelihood ratio, goodness of fit, and hit rate. It was verified that the structure of the model is reasonable, and the upper and lower levels are both significant. The detailed results of inclusive value, likelihood ratio, and goodness of fit are omitted here. Taking the individual traveler as the unit, comparing the choice model predicted the actual choices respondents made. The predicted hit ratio of the model's upper and lower levels is shown in Table 7.

Table 7. Prediction hit rate of model.

Lower Model								
Travel Mode	Prediction Results						Total	
	Walking	Public Bicycle	Mobike	ofo	Transit	Subway		
Actual choice	Walking	211 (85.4%)	4	6	14	2	0	237
	Public bicycle	1	7 (58.3%)	0	1	0	0	13
	Mobike	8	0	51 (72.9%)	2	0	0	61
	ofo	24	1	12	117 (86.0%)	1	0	138
	Transit	2	0	1	1	21 (84.0%)	1	26
	Subway	1	0	0	1	1	26 (96.3%)	29
	Total	247	12	70	136	25	27	517 (83.7%)
Upper model								
Riding frequency	Prediction results			Total				
	≤ 0.5	0.5–1	> 1					
Actual choice	≤ 0.5	82 (82%)	9	7	98			
	0.5–1	15	185 (78.39%)	44	244			
	> 1	3	42	130 (71.82%)	175			
	Total	100	236	181	517 (76.8%)			

In Table 7, the data on the diagonal is the number of hits (hit rate) in the corresponding travel mode/riding frequency. Further analysis shows that the comprehensive hit rates of the upper and lower level models are 76.8% and 83.7%, respectively, and the NL model has high comprehensive prediction accuracy. In each individual forecast, the model maintains single forecast accuracy of more than 70% except for public bicycles. By analyzing questionnaire and forecast data, it is found that public bicycles had a small share of travel in the survey (only seven trips), which caused low prediction accuracy of the model.

4. Discussion and Conclusions

Based on the revealed preference (RP) questionnaire data, this paper used the cross-analysis method to analyze the personal features, riding habits, and trip characteristics of shared bicycle users. Using the factor analysis method, this paper deals with the original influencing factors. The common factor with significant influence was selected as the subsequent modeling-explanatory variable, to realize the dimensionality reduction of explanatory variables, and the continuous variation

of discrete variables. The double-layer NL model of riding frequency–travel mode was established to form a comprehensive description of the characteristics of shared bicycle users. The results show the following:

(1) By restoring explanatory variables and sensitivity analysis, the results show that the main reasons for riding shared bicycles are low cost, flexibility, the ability to avoid traffic congestion, ease of use, low carbon impact, close proximity, and lack of transport. Important factors influencing the choice of cycle types are that they are accessible, easy to find, and economical; they have deposit safety and are comfortable. Additionally, special offers; cycling experience; and bicycle quality were important factors. Increasing the level of bicycle service can enable walkers to shift to riding. Ofo's bicycle sharing rate is more sensitive to service level than Mobike's. Bicycle usage has dropped sharply with increased riding cost. Perfecting the nonmotor vehicle lane transportation facilities of roads and improving the safety of the riding environment can significantly promote bicycle utilization.

(2) Results also indicate that the daily riding environmental factors represented by "flat road" and "complete and clear markings and signs" have a significant impact on the choice of travel mode and riding frequency. With the optimization of the riding environment, the middle- and high-level riding frequency groups have significantly increased, accompanied by a proportion of low-level riding frequency shifts. In addition, with the optimization of "flat road," the walking share decreased significantly, ofo's share decreased slightly, and Mobike's share increased significantly. This is in line with the situation—Mobike has better-quality bicycles than ofo, but the body is heavier, and travelers on slopes tend to choose Mobike, while on complex roads they tend to choose ofo.

The findings of this study emphasize the importance of the combination of the NL model and factor analysis in the study of travel behavior. At present, there are many specific studies on travel mode choice, riding frequency, riding characteristics, and factors that affect riding. However, there is still a lack of comprehensive research that combines travel characteristics of users, influencing factors, travel modes, and riding frequency. In addition, in the selection of influencing factors and the setting of model independent variables, the common method is still to use basic survey information processed by statistical analysis and then directly use that for modeling. Independence between variables depends entirely on the quality of the original data, which often leads to serious multicollinearity problems. In this paper, correlation analysis is used to reasonably allocate original explanatory variables in the upper and lower layers of the NL model. Factor analysis is typically used to reconstruct explanatory variables, while this paper retains the effective information of the original survey and removes the potential correlation between variables, thereby avoiding potential serious multicollinearity problems.

However, the limitations in this study should be recognized. Although a relatively complete independent variable selection, configuration, and reconstruction process was formed, in the setting of the basic questionnaire, some of the content was repeated as an option and question (in a scenario); that was a defect in the form of information crossover. In addition, due to the influence of the survey time (winter), the travel data cannot represent the riding habits and daily travels of college students in other seasons. The model established by stated preference survey data still has a certain degree of limitations to its applicability and objectivity. Therefore, in subsequent work, the riding habits and travel survey data of every season should be added to the comprehensive modeling process, and we will try to use the orthogonal design method to build questionnaires to make the survey information more comprehensive and targeted.

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Appendix A Travel Characteristics Data

Table A1. Distribution of respondents' individual characteristics.

Survey Content	Option	Sample	Percent	Survey Content	Option	Sample	Percent
Gender	Male	305	63.1%	Will pay attention to environmental news/events	Yes	357	73.9%
	Female	178	36.9%		No	96	26.1%
Education	Undergraduate	204	42.2%	Can ride bicycle	Yes	476	98.6%
	Postgraduate	279	57.8%		No	7	1.4%
Sports frequency	Rarely	109	22.6%	Has public bicycle IC card	Yes	122	25.3%
	Occasionally	253	52.4%		No	361	74.7%
	Often	121	25.0%		Neither	42	8.7%
Disposable living expenses (yuan)	≤1000	126	26.1%	Installed bicycle sharing app	Only Mobike	239	31.5%
	1000–1500	239	49.5%		Only ofo	133	45.4%
	1500–2000	75	15.5%		Both	70	14.4%
	≥2000	43	9.0%		Yes	72	14.9%
Waiting for traffic lights and walking on crosswalks	Will not	5	1.1%	Has personal bicycle	No	411	85.1%
	Will if police nearby	11	2.2%		Very unsupported	12	2.4%
	Sometimes will	39	8.2%		Unsupported	11	2.2%
Has environmental awareness	Will	428	88.6%	Cycling support level	Supported	337	69.8%
	Yes	446	92.4%		Very supported	123	25.5%
	No	21	4.3%				
	Not clear	16	3.3%				

Note: A public bicycle IC card is a value card similar to a bus IC card, which can be used in conjunction with the urban public bicycle system.

Table A2. Distribution of respondents' riding habits.

Survey Content	Option	Sample	Percent	Survey Content	Option	Sample	Percent
Riding frequency	≤0.5	106	22.0%	Acceptable search time (min)	1	27	5.7%
	1	222	45.9%		2	42	8.7%
	≥2	155	32.1%		3	60	12.4%
Riding time/period	Only day	182	37.7%	5	249	51.5%	
	Only night	7	1.4%	10	90	18.7%	
	Day and night	294	60.9%	>10	15	3%	
Acceptable riding time (min)	≤10	42	8.7%	Road safety evaluation	Very low	41	8.5%
	≤15	190	39.4%		Low	249	51.5%
	≤20	143	29.6%		High	181	37.5%
	>20	108	22.3%		Very high	12	2.5%
Acceptable cycling distance (km)	1	26	5.3%	Satisfaction of riding environment (scores)	0, 1, 2	31	6.4%
	2	180	37.3%		3	39	8.1%
	3	173	35.9%		4	52	10.7%
	>3	104	21.5%		5	83	17.2%
Search time before riding (min)	1	66	13.6%	6	79	16.4%	
	2	121	25.0%	7	82	17.0%	
	3	98	20.3%	8	68	14.0%	
	5	146	30.4%	9, 10	49	10.2%	
	10	45	9.5%				
	>10	7	1.4%				

Appendix B Correlation Test Results

Table A3. Correlation test of travel mode and influence factors.

Variable Category	Original Influence Factor (Code)	Type	Spearman Coefficient	Sig.	Variable Category	Original Influence Factor (Code)	Type	Spearman Coefficient	Sig.									
(1) Personal features and travel mode																		
Gender	Male (Z1)	0–1	0.091 *	0.039	Education	Undergraduate (Z3)	0–1	0.098 *	0.026									
	Female (Z2)	0–1	−0.091 *	0.039		Postgraduate (Z4)	0–1	0.098 *	0.026									
Environmental awareness	Will pay attention to environmental news or not (Z5)	0–1	0.141 **	0.001	Riding frequency	Daily riding frequency (Z6)	Continuous	0.114 **	0.010									
(2) Riding habits and travel mode																		
Cycling expectations	Acceptable cycling distance < 2 km (Z8)	0–1	0.051 *	0.046	Cycling reasons	Cheap (Z22)	0–1	−0.092 *	0.036									
	Acceptable cycling distance < 3 km (Z9)	0–1	0.117 *	0.010		Flexible (Z23)	0–1	−0.077	0.036									
	Acceptable cycling distance > 3 km (Z10)	0–1	0.112 *	0.030		Low carbon (Z24)	0–1	0.128 **	0.003									
	Acceptable riding time (Z11)	Ordered	−0.0109 *	0.013		Avoid traffic congestion (Z25)	0–1	0.093 *	0.035									
Cycling experiences	Acceptable searching time (Z12)	Ordered	−0.110 *	0.012	Cycling season	Lack of transport (Z26)	0–1	0.115 *	0.017									
	Road safety evaluation (Z7)	Ordered	0.111 *	0.012		Summer only (Z27)	0–1	−0.106 *	0.016									
	Operational convenience (Z13)	Ordered	−0.110 *	0.012		Autumn only (Z28)	0–1	−0.094 *	0.033									
	Searching convenience (Z14)	Ordered	−0.164 **	0.000	Except winter (Z29)	0–1	−0.176 **	0.000										
	Returning convenience (Z15)	Ordered	−0.096 *	0.028	All seasons (Z30)	0–1	0.248 **	0.000										
	Bicycle quality scores (Z16)	Ordered	−0.208 **	0.000	Daily riding time	Only day (Z31)	0–1	−0.165 **	0.000									
	Deposit security scores (Z17)	Ordered	−0.152 **	0.001		Day and night (Z32)	0–1	0.169 **	0.000									
Riding promotion scores (Z18)	Ordered	−0.137 **	0.002	Isolated bicycle lane (Z33)		0–1	0.093 *	0.035										
Overall satisfaction scores (Z19)	Ordered	−0.171 **	0.000	Signal lights at intersections (Z34)		0–1	−0.119 **	0.007										
Traveling purpose	Attending class (Z20)	0–1	−0.136 **	0.002	Daily riding environment	Flat road (Z35)	0–1	0.042 *	0.038									
	Transferring (Z21)	0–1	0.099 *	0.025		Campus interior (Z36)	0–1	−0.115 **	0.009									
(3) Trip information and travel mode	Traveling characteristics	Traveling road environment	Traveling road environment	Traveling road environment		Traveling road environment	Traveling road environment	Traveling road environment	Traveling road environment	Traveling road environment	Traveling road environment							
					Entertainment (Z38)							0–1	−0.149 **	0.001	Bicycle lanes (Z48)	0–1	0.107 *	0.015
					Shopping (Z39)							0–1	0.105 *	0.044	Road congestion (Z49)	0–1	0.463 **	0.000
					Returning (Z40)							0–1	−0.082 *	0.031	Many cars (Z50)	0–1	0.428 **	0.000
					Visiting friends (Z41)							0–1	0.098 *	0.026	Many pedestrians (Z51)	0–1	0.106 *	0.016
					Laboratory attendance (Z42)							0–1	0.174 **	0.000	Many intersections (Z52)	0–1	0.237 **	0.000
	Travel time (min) (Z43)	Continuous	0.229 **	0.000	Flat road (Z53)	0–1	0.098 *	0.027										
	Travel distance (km) (Z44)	Continuous	0.533 **	0.000	Through pedestrian bridge (Z54)	0–1	0.117 **	0.008										
	Traveling natural environment	Cloudy (Z45)	0–1	0.180 **	0.000	Complete and clear markings and signs (Z55)	0–1	0.376 **	0.000									
		Sunny (Z46)	0–1	−0.169 **	0.000	Trips on campus (Z56)	0–1	−0.121 **	0.006									
Perceived temperature (Z47)		0–1	−0.116 **	0.008														

Note: ** Significantly correlated at the 0.01 level (two-sided); * significantly correlated at the 0.05 level (two-sided).

Table A4. Correlation test of riding frequency and influence factors.

Variable Category	Original Influence Factor (Influence Factor Code)	Type	Spearman Coefficient	Sig.	Variable Category	Original Influence Factor	Type	Spearman Coefficient	Sig.
(1) Personal features and riding frequency									
Gender	Male (M1)	0–1	0.183 **	0.000	Disposable living expenses	1000–1500 (yuan) (M11)	0–1	−0.142 **	0.001
	Female (M2)	0–1	−0.183 **	0.000		1500–2000 (yuan) (M12)	0–1	0.147 **	0.001
Sports frequency	Rarely (M3)	0–1	−0.116 **	0.009	IC card	Has bus IC card (M6)	0–1	0.146 **	0.001
	Occasionally (M4)	0–1	0.106 *	0.016	Bicycle usage	As major travel mode (M7)	0–1	0.426 **	0.000
Installed bicycle sharing app	Neither (M8)	0–1	0.089 *	0.043	Environmental awareness	Will pay attention to environmental news or not (M5)	0–1	0.115 **	0.009
	Only ofo (M9)	0–1	0.125 **	0.005					
	Both (M10)	0–1	−0.208 **	0.000					
(2) Riding habits and riding frequency									
Daily riding time	Only day (M13)	0–1	−0.293 **	0.000	Cycling reasons	Cheap (M25)	0–1	0.192 **	0.000
	Day and night (M14)	0–1	0.299 **	0.000		Habit (M26)	0–1	0.173 **	0.000
Cycling expectations	Acceptable riding time (M15)	Ordered	0.123 **	0.005		Low carbon (M27)	0–1	0.199 **	0.000
	Acceptable searching time (M16)	Ordered	0.132 **	0.003		Avoid traffic congestion (M28)	0–1	0.125 **	0.005
Cycling season	Summer only (M17)	0–1	−0.135 **	0.002		For exercise (M29)	0–1	0.088 *	0.046
	All seasons (M18)	0–1	0.120 **	0.007		Isolated bicycle lane (M30)	0–1	0.091 *	0.040
Travel purpose	Spring and autumn (M19)	0–1	−0.131 **	0.003	Daily riding environment	Mixed traffic (M31)	0–1	−0.096 *	0.030
	Attending class (M20)	0–1	0.297 **	0.000		Signal lights at intersections (M32)	0–1	0.134 **	0.002
	Shopping (M21)	0–1	0.112 *	0.011		Not pass pedestrian bridge (M33)	0–1	0.106 *	0.016
Daily bicycle riding	Public bicycle (M22)	0–1	0.155 **	0.000	Traveling road environment	Campus interior (M34)	0–1	0.093 *	0.036
	Mobike (M23)	0–1	0.110 *	0.012		Road congestion (M35)	0–1	0.161 **	0.000
	ofo (M24)	0–1	−0.092 *	0.038		Trips on campus (M36)	0–1	0.114 **	0.010

Note: ** Significantly correlated at the 0.01 level (two-sided); * significantly correlated at the 0.05 level (two-sided).

Table A5. Common factor definitions and reliability test.

Lower Model			
Common Factor Code	Renamed Common Factor	Expression	Cronbach α Reliability Coefficient
x ₁	Cycling experiences factor	$x_1 = 0.207Z_{13} + 0.201Z_{14} + 0.207Z_{15} + 0.160Z_{16} + 0.173Z_{17} + 0.182Z_{18} + 0.208Z_{19}$	0.857
x ₂	Traveling road environment factor 1	$x_2 = 0.173Z_{48} + 0.262Z_{51} + 0.215Z_{52} - 0.309Z_{56}$	0.704
x ₃	Traveling road environment factor 2	$x_3 = 0.234Z_{39} + 0.253Z_{50} + 0.240Z_{53} - 0.270Z_{54} + 0.232Z_{55}$	0.748
x ₄	Traveling characteristics factor	$x_4 = 0.296Z_{43} + 0.348Z_{44} + 0.208Z_{49}$	0.801
x ₅	Daily riding time factor 1	$x_5 = -0.401Z_{31} + 0.412Z_{32}$	0.823
x ₆	Gender factor 1	$x_6 = 0.475Z_1 - 0.475Z_2$	0.743
x ₇	Education factor 1	$x_7 = -0.389Z_3 + 0.389Z_4$	0.798
x ₈	Cycling expectation factor 1	$x_8 = 0.465Z_{10} + 0.446Z_{11}$	0.720
x ₉	Traveling natural environment factor	$x_9 = 0.404Z_{45} - 0.399Z_{46} - 0.35Z_{47}$	0.827
x ₁₀	Cycling expectation factor 2	$x_{10} = -0.463Z_8 + 0.520Z_9$	0.767
x ₁₁	Cycling season factor 1	$x_{11} = -0.464Z_{29} + 0.369Z_{30}$	0.832
x ₁₂	Comprehensive factor 1	$x_{12} = 0.416Z_{21} + 0.266Z_{24} - 0.418Z_{26} - 0.141Z_{28} + 0.204Z_{33}$	0.661
x ₁₃	Comprehensive factor 2	$x_{13} = 0.449Z_6 + 0.297Z_{20}$	0.773
x ₁₄	Daily riding environment factor 1	$x_{14} = 0.331Z_{25} + 0.436Z_{34} + 0.274Z_{35}$	0.804
x ₁₅	Comprehensive factor 3	$x_{15} = 0.269Z_5 - 0.468Z_{37} + 0.404Z_{42}$	0.693
x ₁₆	Traveling purpose factor 1	$x_{16} = 0.434Z_{38} - 0.56Z_{40}$	0.819
x ₁₇	Cycling season factor 2	$x_{17} = 0.541Z_{27}$	–
x ₁₈	Comprehensive factor 4	$x_{18} = 0.327Z_7 + 0.191Z_{12} + 0.502Z_{23}$	0.732
x ₁₉	Traveling purpose factor 2	$x_{19} = -0.566Z_{41}$	–
Upper model			
w ₁	Daily riding time factor 2	$w_1 = -0.399M_{13} + 0.399M_{14}$	0.823
w ₂	Gender factor 2	$w_2 = 0.445M_1 - 0.445M_2$	0.743
w ₃	Comprehensive factor 5	$w_3 = -0.493M_8 - 0.445M_{24}$	0.657
w ₄	Comprehensive factor 6	$w_4 = 0.511M_9 + 0.462M_{23}$	0.710
w ₅	Education factor 2	$w_5 = 0.511M_3 - 0.547M_4$	0.798
w ₆	Disposable living expenses factor	$w_6 = -0.561M_{11} + 0.531M_{12}$	0.836
w ₇	Comprehensive factor 7	$w_7 = 0.205M_7 + 0.427M_{21} + 0.428M_{29}$	0.749
w ₈	Daily riding environment factor 2	$w_8 = 0.554M_{34} + 0.503M_{36}$	0.715
w ₉	Comprehensive factor 8	$w_9 = 0.272M_{18} - 0.364M_{19} + 0.365M_{25} + 0.44M_{30}$	0.802
w ₁₀	Comprehensive factor 9	$w_{10} = -0.329M_{10} - 0.547M_{17} + 0.267M_{20}$	0.735
w ₁₁	Comprehensive factor 10	$w_{11} = 0.351M_5 - 0.339M_{26} + 0.411M_{32} + 0.353M_{35}$	0.651
w ₁₂	Public bicycle factor	$w_{12} = 0.376M_6 + 0.497M_{22}$	0.809
w ₁₃	Cycling reasons factor	$w_{13} = 0.613M_{27} + 0.210M_{28}$	0.763
w ₁₄	Cycling expectation factor 3	$w_{14} = 0.574M_{15} + 0.506M_{16}$	0.776
w ₁₅	Daily riding environment factor 3	$w_{15} = -0.507M_{31} + 0.632M_{33}$	0.808

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