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Analysis and modeling of residents travel behavior under MaaS

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Abstract: The swift advancement of urban motorization has resulted in a disparity between the supply and demand of traffic services. The conventional travel service framework has proven inadequate in facilitating a seamless integration of various transportation modes, thereby rendering travel inconvenient for urban residents. Mobility as a Service (MaaS) represents an innovative transportation solution that offers quicker, more efficient, and cost-effective travel alternatives. Nonetheless, the effectiveness of the MaaS system is contingent upon travelers' acceptance and their perceived preferences regarding MaaS. Consequently, this study categorizes travel choice modes within the context of MaaS and develops multinomial logit (MNL) models. Acknowledging the limitations inherent in MNL models, this research proposes enhancements by incorporating random parameters to formulate a mixed logit (MXL) model. A comparative analysis of the parameter estimation outcomes from both the MNL and MXL models reveals an improved interpretative capacity when accounting for heterogeneity. Furthermore, the findings derived from the MXL model indicate that latent influencing factors, such as punctuality, significantly impact travel choices within the MaaS framework. Theoretically, this study offers a valuable reference for quantifying the potential perceptions associated with MaaS travel modes. Practically, the classification of potential travelers aids in identifying early adopters of MaaS and facilitates targeted promotion of MaaS to specific demographic groups, thereby mitigating resistance to its implementation.

Keywords: intelligent transport; MaaS; travel behavior; multiple logit model; mixed logit model; influencing factors

1 Introduction

Decades of car-oriented urban growth have resulted in notable sustainability problems. The increase in motor vehicles has led to an existing mismatch between transport supply and demand, traffic congestion problems got much worsen. To address these problems, priority should be given to public transport and the attractiveness of public transport should be increased. It is common for travelers to transfer between the various modes of transport. However, effective connections are difficult to form, and the level of service and attractiveness provided by existing modes of travel is not significant. The problem of inconvenient travel for residents is still not effectively addressed[1]. Aiming to promote sustainability and integrating various modes of transport travel for optimal mobility by encouraging the use of sustainable transportation and reducing reliance on private cars, Mobility as a Service (MaaS), has garnered considerable attention in the transportation industry[2-4].

The concept of MaaS was first proposed by Hietanen at the European Conference on Intelligent Transport Systems (ITS) in Finland in 2014[5]. MaaS is defined as a travel service system integrating various forms of transport services. Previous studies on the willingness to accept Maas considered two aspects. Based on the platform, the factors studied mainly focused on the easiness and usefulness of the system, as well as the price, diversity, and flexibility of the travel options. From the perspective of users, the factors studied included personal attributes, psychological factors, attitude factors, and personal values[6-7]. The factors mentioned above all have a significant impact on travelers' willingness to use MaaS. The relevant research in China started relatively late, and the existing literature mainly summarized and analyzed foreign cases and explored the development path of MaaS in China, but there were fewer studies on the influence of willingness to use MaaS. Moreover, users' pref-

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erence for travel options under MaaS was mainly based on a discrete choice model by stated preference survey in previous research[8-10].

MaaS has the potential to influence travel behavior[11], reduce private car use, and encourage users to adopt alternative modes of transportation[12-13]. However, the extent of these changes and their direction remains uncertain, necessitating further quantitative analysis[14]. Firstly, MaaS offers personalized services and greater travel convenience through seamless integration[15]. Secondly, MaaS provides travelers with a viable and durable alternative to car travel, which is economically feasible[16]. Thirdly, meeting travelers' demands for autonomy, flexibility, and reliability is an advantage of MaaS, but the acceptance and satisfaction of travelers are difficult to determine[17]. The MaaS pilot shows that freedom of choice, tailored services, and increased mobility can have a positive impact on the adoption of MaaS[18]. This demand for a "tailor-made full service" is especially effective if the requested price is higher than what travelers are used to[19]. Attitude studies and stated preference studies are the primary methods of obtaining information about MaaS[20-21].

Research on the connection between travel behavior and MaaS preferences reveals that as travel patterns evolve, the prerequisites for successful MaaS implementation will also change. These studies offer qualitative insights into the potential user base and overall impact. MaaS aims to provide faster, more convenient, and cost-effective sustainable travel options, while reducing the reliance on private vehicles[17]. However, the effectiveness of MaaS depends on travelers' acceptance and perceived preferences[18]. To a large extent, the promotion of MaaS depends on people's attitudes toward private cars. Therefore, this study aims to the impact of MaaS on travel mode choice behavior, providing theoretical support and policy recommendations for its promotion.

2 Methodology

2.1 Survey and sample description

2.1.1 Data collection

According to the travel mode cholee fetors shown in Figure 1, the questionnaire is structured around three primary aspects, which is presented in detail in Figure2:

(1) Individual attributes, such as gender, age, occupa-

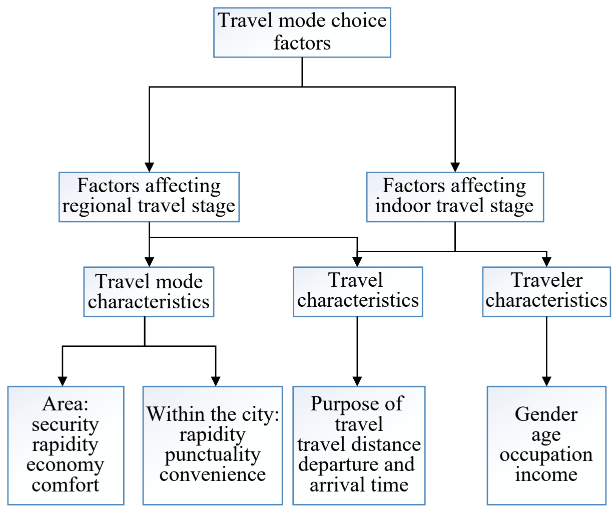

Fig. 1 Travel mode choice factors

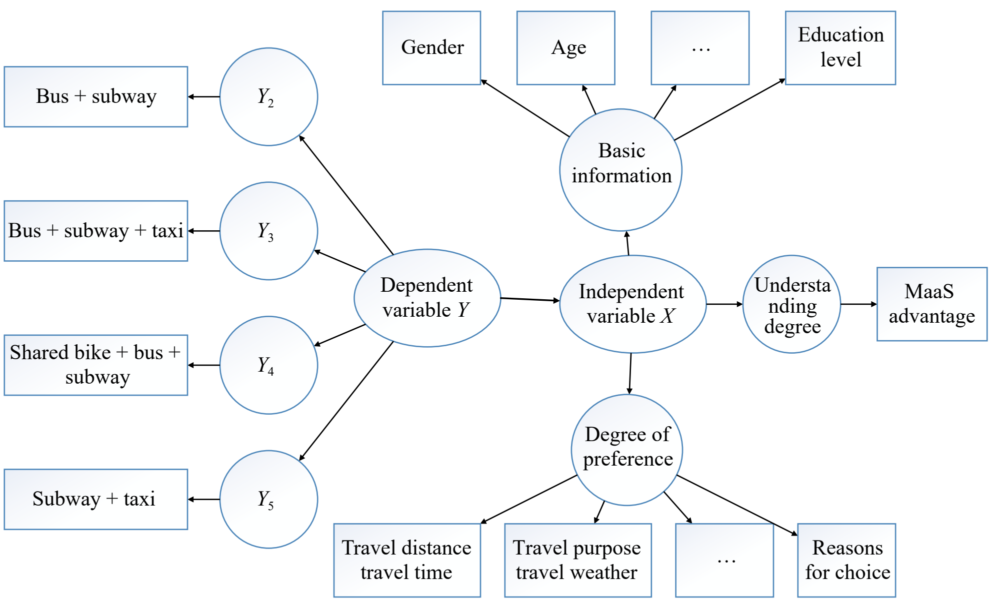

Fig. 2 Questionnaire structure

tion, education level, income, and expenditure.

(2) Individual travel details, including travel frequency, private car ownership, preferred travel modes, and travel purpose.

(3) Attitudes towards MaaS, including acceptance level, travel times, and expected benefits. The preliminary analysis of the data suggests that the quantity and quality of effective questionnaires meet the necessary requirements, covering a broad range of ages and occupations, amongst others, and thus provide a comprehensive and suitable source of data for subsequent modeling[22-23].

The data is based on residents in Beijing. An online survey is conducted with the help of questionnaire stars and a total of 300 questionnaires are collected. First of all, the quality of 300 questionnaires is tested. Three screening principles are determined from the time of answering the questionnaire and the common screening principles of the questionnaire survey. In the end, 290 valid questionnaires are retained, with an effective rate of 96.7%.

2.1.2 Data analysis

Reliability analysis is mainly used to test the reliability of questionnaire sample results. If the Cronbach reliability coefficient (Cronbach α) is higher than 0.8, the effect is better. Between 0.7 and 0.8; the effect is good. Cronbach α coefficient is 0.768, so it can be considered that the reliability level of this data is high. Validity analysis is mainly to test data to explain whether the research is meaningful. Kaiser-Meyer-Olkin (KMO) value is used to judge the degree of information adaptation. If KMO>0.8, it indicates that the data is very suitable; if 0.7<KMO<0.8, the data is suitable. KMO value is 0.735, which indicates that information can be effectively extracted from this data.

Cross-analysis is used to study the different relationships between travel mode and independent variables such as education level and travel times. Taking education level as an example, it can be seen from Figure 3 that samples of different travel modes have different effects on education level.

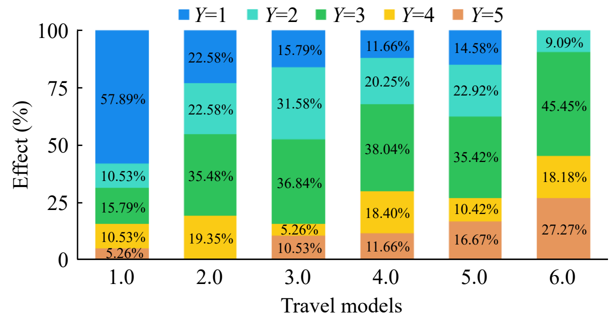

Fig. 3 Cross graph of education level and travel mode

2.2 Modeling and analysis based on MNL model

2.2.1 MNL model

The prediction accuracy of the multinomial logit (MNL) model is higher than that of traditional aggregate model. When the category of dependent variables is three or above and there is no obvious primary and secondary order among dependent variables, the MNL model is more suitable and can obtain the correlation and influence between independent and dependent variables[24]. The utility function of the MNL model is defined as the quantitative relationship between the travel combination mode and the research factors, and the influencing factors of each travel combination mode are explained by a separate utility function. The utility functions of the MNL model are shown in Equations (1) and (2) .

$$U_{ij} = V_{ij} + \varepsilon_{ij}, \tag{1}$$

$$V_{ij} = \beta_i X_{ij}, \tag{2}$$

where, U_{ij} is traveler j corresponds to the utility function of travel mode i; V_{ij} is the definite part of a utility function, usually in linear form; ε_{ij} is random error term, subject to extreme distribution; β_i is the parameters of influencing factors of travel mode i; X_{ij} is independent variable affecting travel mode i.

As a random error term, it is generally assumed that ε_{ij} follows the extreme value distribution. In this case, the MNL model is shown in Equation (3).

$$P_j(i) = \frac{\exp\left(\beta_i X_{ij}\right)}{\sum \exp\left(\beta_i X_{ij}\right)}, \tag{3}$$

where $P_j(i)$ is the likelihood of traveler j choosing travel mode i.

The MNL model modeling steps are shown in Figure 4.

Travel choice mode is taken as dependent variable Y to study the influencing factors of residents' travel choice behavior. The specific variable Settings are shown in Table 1.

2.2.2 Parameter estimation

For the preliminary selection of modeling variables,

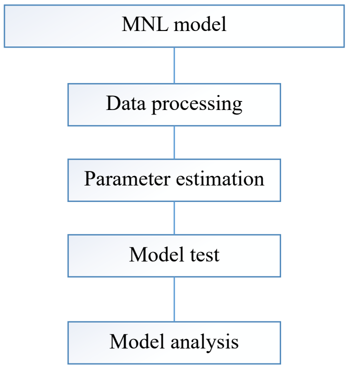

Fig. 4 MNL model modeling steps

the combination of independent variables of the preliminary model is determined, and a number of logit models are constructed using Stata, with a significance level of 0.05. Based on this, the influence degree of independent variables on dependent variables is judged, so that the factors in the combination of independent variables are adjusted accordingly, and the model is improved step by step until the most effective is achieved. A significant combination of influencing factors is obtained.

The results of parameter estimation are shown in Table 2. Pseudo-r square outputs three indicators, among which McFadden serves as the likelihood ratio index. Generally speaking, the larger the value, the better the model fitting, and the test results show that the independent variable in the model has better explanatory ability than the dependent variable.

2.3 Modeling and analysis based on MXL model

2.3.1 MXL model

Although MNL model is often used in prediction and analysis of travel behavior and is relatively mature, it has some limitations. Despite its relative maturity, the model does not account for the independence of irrelevant alternatives (IIA), and the model may not capture differences among individuals.

According to the structure of MNL model, in the tradi-

Table 1 Variable setting

Class	Variable	Definition	Value
Dependent variable	Y	Preferred mode of travel to choose MaaS	1, Private car, 2, Bus+subway, 3, Bus+Subway+Taxi, 4, Shared Bike+Bus + Subway, and 5, Subway +Taxi
Individual socioeconomic attributes	X_1	Gender	1, Male and 2, Female
	X_2	Age	1, 18 to under, 2, 18 to 25, 3, 26 to 30, 4, 31 to 40, and 5, 41 and over
	X_3	Occupation	1, Student, 2, Institution staff, 3, Freelancer, 4, Service staff, and 5, Enterprise staff
	X_4	Education level	1, Junior high School and below, 2, High school, 3, Junior College, 4, Bachelor’s, 5, Master, and 6, Doctor
	X_5	Monthly income	1, Below 5 000 yuan, 2, CNY5 000 to CNY7 000 yuan, 3, CNY7 000 to CNY9 000 yuan, 4, CNY9 000 to CNY11 000, and 5, CNY11 000 or more
	X_6	Number of private cars	1, None, 2, 1 Cars, 3, 2 Cars, and 4, 3 Cars and above
	X_7	Monthly living expenses	1, Less than CNY1 000 yuan, 2, CNY1 000 to CNY2 000, 3, CNY2 000 to CNY4 000, 4, CNY4 000 to CNY6 000, 5, CNY6 000 to CNY10 000, and 6, more than CNY10 000
	X_8	Monthly traffic expenditure	1, CNY100 or less, 2, CNY100 to CNY300, 3, CNY300 to CNY500, 4, CNY500 to CNY1 000, and 5, CNY1 000 or more
Scene factor	X_9	MaaS advantage	1, convenience, 2, punctuality, 3, comfort, and 4, economy
	X_{10}	Be willing to try new things	1, not willing, 2, basically not willing, 3, fair, 4, willing, and 5, more willing
	X_{11}	What weather will choose MaaS	1, bad weather, 2, fair weather, and 3, comfortable weather
	X_{12}	When will MaaS be selected	1, early morning, 2, morning, 3, afternoon, and 4, night
	X_{13}	What travel purpose will choose MaaS	1, school, 2, work, 3, business, 4, travel and recreation, and 5, visiting friends and family
	X_{14}	Reasons for choosing MaaS	1, price, 2, weather, 3, time, 4, distance, and 5, environmental protection

Table 2 Parameter estimation

Y	Regression coefficient	Standard deviation	z	χ^2	p	OR
Occupation	−0.272	0.275	−0.990	0.980	0.322	0.762
Educational level	0.433	0.217	1.996	3.982	0.046	1.542
Monthly income	0.752	0.415	1.812	3.284	0.070	2.121
Private car	−0.162	0.391	−0.414	0.172	0.679	0.850
Cost of living	−0.401	0.293	−1.369	1.874	0.171	0.670
Traffic overhead	−0.395	0.295	−1.336	1.786	0.181	0.674
Number of trips	0.394	0.196	2.006	4.025	0.045	1.482
Understanding degree	0.055	0.166	0.331	0.109	0.741	1.057
Intercept	−1.028	1.197	−0.858	0.737	0.391	0.358

tional sense, the model assumes that the parameter β_i of all independent variables is a fixed value. However, in practical situations, the travel process is very complicated, which is comprehensively affected by many factors. In addition, major factors should be taken into account in the construction of the model, and all potential factors cannot be included.

Aiming at addressing the problem of fixed values of the above parameters, random parameters were introduced to construct a mixed logit (MXL) model, to achieve the purpose of random variation of the effect of dependent variables, making the effect of the same influencing factor more consistent with the real situation in the actual travel selection. For a certain factor in the model, the effect of different travel modes can not only consider the influence of potential factors, but also take into account the influence of research factors.

The MXL model is constructed to enable parameter variations among different travel modes in MNL models. Mixed distribution is introduced, which can consider the heterogeneity among different samples and the correlation between different choices. The coefficient β_i of the independent variable in the original model is redefined as shown in Equation (4).

$$\beta_i = \beta + \Gamma \mu_{ij}, \tag{4}$$

where, β is the mean value of the estimation coefficient of independent variable; Γ is coefficient matrix of random parameters; μ_{ij} is the random error follows a normal distribution.

In this case, the coefficient of the independent variable is a linear representation of the estimated mean β and the random error μ_{ij}, so that the coefficient of the independent variable can take into account the heterogeneity among different samples ignored by MNL model. The resulting mode probability $P_{ij}|\beta_j$ as shown in Equation (5).

$$P_{ij}|\beta_j = \int \frac{\exp\left(\beta_j X_{ij}\right)}{\sum_{j=1}^{k} \exp\left(\beta_j X_{ij}\right)} f(\beta|\theta)\,\mathrm{d}(\beta), \tag{5}$$

where, $f(\beta|\theta)$ is β probability density function, usually assumed to obey normal distribution; θ is parameter of distribution.

2.3.2 Parameter estimation

The primary distinction between the MXL model and other logit models lies in the method of parameter estimation. The parameter estimation method adopted by the MNL model is the maximum likelihood method mentioned in the previous paper, but this method is not applicable because the probability function of the MXL model is non-closed. Therefore, it is necessary to set the distribution form of random parameters in MXL model. The distribution of random parameters in Stata is normally distributed by default, and the sampling method is Halton sampling.

The goodness-of-fit of the model is shown in Table 3, which can be used to analyze the effectiveness of the overall model. The model fitting information shows that the significant value is less than 0.05, indicating that the model is effective and the fitting results are meaningful. The model likelihood ratio test results showed that the goodness-of-fit was 0.327 and the significance level was 0.000, so the independent variables in the model had a significant impact on the dependent variables.

Table 3 Parameter estimation

Y=2	Standard deviation	z	χ^2	p	OR
Education level	0.213	1.947	4.134	0.032	1.012−1.918
Price	0.462	2.467	7.556	0.004	1.489−9.582
Distance	0.478	0.982	0.783	0.250	0.531−3.290
Punctuality	0.653	2.012	3.562	0.000	1.234−5.782

The results of parameter estimation are shown in Table 4. The results show that the model has good fit-

Table 4 Likelihood ratio test

	Logarithmic likelihood value	χ^2	ρ^2	p	*AIC*	*BIC*
Intercept	−513.303					
Final model	−482.439	73.864	0.327	0.000	854.439	1 003.906

ting effect, can explain the relationship between independent variable and dependent variable better, and can further analyze the model results[25].

3 Results and discussion

3.1 The result analysis of MNL model

The goodness-of-fit of the model is shown in Table 5, which can be used to analyze the effectiveness of the overall model. In the process of model modification, AIC and BIC values are used as the comparison reference for model fitting effect after each modification. The decrease in AIC and BIC values indicates that the model modification is effective. The significant value is less than 0.05, indicating that the model is effective and the fitting results are meaningful. The model likelihood ratio test results show that the significance level is 0.000, so the independent variable in the model has a significant impact on the dependent variable.

Table 5 Likelihood ratio test

Cox and Snell	Nagelkerke	McFadden
0.393	0.422	0.594

The results show that the model performs well in fitting effect, can explain the relationship between the independent variable and dependent variable better, and can further analyze the model results. Significant influencing factors are presented in Table 6, showing that education level, rain and snow weather, price and distance have significant effects on travel mode choice. The detailed analysis is shown as follows:

Table 6 Significant influencing factors

	Y=2	*Y*=3	*Y*=4	*Y*=5
Education level	0.349*	0.421*	0.326	0.833*
Rain and snow weather	1.118*	1.940*	0.836	1.717*
Price	1.351*	1.274*	1.062*	1.774*
Distance	−0.363	−1.250*	−1.262*	−0.839
Intercept	−1.102	−0.958	−1.425	−2.146
Likelihood ratio test	$\chi^2(16)=73.864$, $p=0.000$			

Significance levels: - not significant, *0.05, **0.01.

(1) Education level, rain and snow weather, price, distance and punctuality have significant effects on travel mode selection. With the increase in education level, people have a high acceptance of “subway + taxi” among the possible travel modes provided by MaaS, while the selection rate of “shared bike + bus + subway” is low.

(2) Rain and snow weather factors have the most significant influence on the travel mode of “bus + subway + taxi”, while the influence on the travel mode of “shared bike + bus + subway” is weak, which is different from common sense. As the weather has a significant impact on the use of shared bike, the “shared bike + bus + subway” mode of travel is more affected by bad weather, which increases the demand for taxis.

(3) The price factor has a significant impact on all travel modes, indicating that travelers’ consideration of travel costs is generally prominent, and the rational use of this result in the promotion for MaaS will play a role in promoting the development of MaaS.

According to the OR (Rdds Ratio) value in Table 2, compared with the private car control group, when the travel mode is “bus + subway”, the influence of education level on the latter group is 1.436 times that of the former group. The influence of rain and snow on the latter is 3.055 times that of the former. The influence of price on the latter is 3.884 times that of the former.

3.2 The result analysis of MXL model

As shown in Table 7, the results indicate that the model has a strong fitting ability, can perform well in explaining the relationship between independent variable and dependent variable, and facilitating further analysis of the model’s results. It can be found that in this model, education level, rain and snow weather, price and distance still have significant effects on travel mode. In addition, the relationship between punctuality and dependent variable is also significant, indicating that punctuality will also affect the choice of travel mode.

In order to compare the fitting effect of MNL model and MXL model, AIC (Akaike Information Criterion) and BIC (Bayesian Information Criterion) index are used as the main reference basis. It can be seen that the AIC of MXL is smaller, because the model performs well It

Table 7 Comparison results of model parameter estimation

Influencing factors	MNL parameter				MXL parameter			
	Y=2	Y=3	Y=4	Y=5	Y=2	Y=3	Y=4	Y=5
Intercept	−1.102	−0.958	−1.425	−2.146	−1.034	−0.798	−1.305	−1.989
Education level	0.349*	0.421*	0.326	0.833*	0.284	0.321	0.282*	0.725*
Rain and snow weather	1.118*	1.940*	0.836	1.717*	1.017	1.826* (0.825)	0.792*	1.651
Price	1.351*	1.274*	1.062*	1.774*	1.218	1.149	0.957*	1.678*
Distance	−0.363	−1.250*	−1.262*	−0.839	−0.429*	−1.410	−1.382*	−0.937
Punctuality	0.852	1.049*	0.581	0.967	0.801*	0.957*	0.512*	0.863*
Logarithmic likelihood Value	−508.636				−482.439			
AIC	889.636				854.439			
BIC	1 021.875				1 003.906			

can be seen from the fitting data of the two models that the fitting accuracy of the improved model is better.

For random parameter analysis, MXL model results show that rain and snow weather for “bus + subway + taxi” is a random parameter, and is a significant influencing variable with a confidence level of 95%. The corresponding parameter distribution follows the normal distribution with a standard deviation of 0.825 and a mean of 1.826, and the proportion of the parameter taking negative value is 17.16%. The relevant explanation is: compared with private car travel, 17.16% of people choose “bus + subway + taxi” travel probability is lower than private car travel, that is, in rain and snow weather, “bus + subway + taxi” use rate is higher.

4 Conclusions

In theory, this paper provides a reference for quantifying the potential perception of MaaS travel modes. In practice, the classification of potential travelers contributes to identifying early MaaS recipients and promoting MaaS to specific groups in a targeted way, which can reduce resistance to MaaS promotion. The main conclusions are as follows:

(1) MaaS system affects residents’ travel choices through education level, rain and snow weather, price and distance. The fitting performance of MXL model is better than that of MNL models. In addition, punctuality can also significantly affect the choice of travel mode, indicating that MaaS system also affects residents’ travel choices through punctuality.

(2) Comparing the parameter estimation results of the MNL model and the MXL model, it can be found that the two models have different research results. The explanatory ability of the MXL model is enhanced. Based on the conclusions of the MNL model, the potential influencing factors are found, punctuality can also affect the travel choice under MaaS. Therefore, the modeling research in this paper is meaningful and necessary.

The characteristics of this research paper are shown as follows:

(1) Study on travel behavior under MaaS. The research on travel behavior is relatively mature. However, the research on the change in travel behavior and its influencing factors under MaaS is relatively weak. Therefore, this paper concentrates on travel behavior after the introduction of MaaS .

(2) Divide the combination of transportation modes and set scene factors. The combination schemes of different transportation modes provided by MaaS in this paper are mainly based on existing studies and schemes. In the questionnaire setting, in order to obtain the personalized choice of MaaS during travel, the hypothetical scenario factors of “MaaS new travel mode” were set.

This study analyzes the factors influencing MaaS travel behavior and provides corresponding policy suggestions. However, there are still limitations. Due to the limitations of online survey data, more accurate studies are expected to be carried out in the development of

MaaS. Due to the limitations of the model, only the Logit-related model is constructed for research, and other models can be considered in the future.

Declaration of competing interest

The authors have no competing interests to declare that are relevant to the content of this article.

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