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Shared Autonomous Vehicles as Last-Mile Public Transport of Metro Trips

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Abstract: The "last-mile problem" of public transportation is one of the main obstacles affecting travelers who choose to utilize public transport. Although autonomous vehicles (AVs) have made much progress, they have not been officially put into commercial use. This paper adopts stated preference experiments to explore the impact of shared AVs on the last-mile travel behavior of metro users and takes Wuhan as an example for case analysis. First of all, this paper establishes a structural equation model (SEM) based on the theory of planned behavior to explore latent psychological variables, including travelers' attitudes (ATTs), subjective norms (SNs), perceived behavior control (PBC), and behavioral intention of use (BIU) toward AVs. These latent psychological variables are incorporated into the latent class (LC) logit model to establish a hybrid model with which to study the factors and degree of influence on the travel mode choices of travelers for the last mile of their metro trips. The results show that travelers have preference heterogeneity for the travel mode choices for the last mile of metro trips. Through the analysis of LCs, education, career, and income significantly impact the classification of LCs. The latent psychological variables towards AVs have a significant impact on the travel behavior of respondents, but the impacts vary among different segments. Elastic analysis results illustrate that a 1% increase in the travel cost for shared AVs in segment 1 leads to a 7.598% decrease in the choice probability of using a shared AV. Respondents from different segments vary significantly in their willingness to pay for their usage, and the value of travel time for high-income groups is relatively higher.

Keywords: autonomous vehicles; last-mile transport; preference heterogeneity; theory of planned behavior; latent class logit model

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1. Introduction

With the rapid and excessive development of motorization, most cities worldwide are confronted with traffic congestion, air deterioration, noise pollution, fossil fuel consumption, and carbon emissions [1]. Public transport, especially the metro, has excellent advantages in alleviating traffic congestion, reducing fossil energy consumption, improving transportation efficiency, and reducing carbon emissions [2]. However, unlike private cars, the metro provides a "station-to-station" service rather than a "door-to-door" service. Therefore, the last-mile problem has become one of the main obstacles for travelers choosing public transport [3,4]. The most common last-mile travel modes include walking, shared bicycles, and buses. However, each mode has its advantages and disadvantages. For example, walking provides excellent flexibility, economy, and environmental friendliness and it benefits the physical and mental health of the traveler [5,6]. However, walking is only suitable for travel within 10 min [7], and its use is restricted in bad weather (e.g., rain and snow). Shared bicycles solve the problems of access and parking, but are likely to cause traffic accidents and traffic congestion [1]. Similar to walking, shared bicycles are also restricted in bad weather. Taking a bus presents the advantages of short travel time and low travel cost, but the walking and waiting times are relatively long, and the attractiveness of taking the bus is not high enough.

Autonomous vehicles rely on artificial intelligence, visual computing, radar, surveillance devices, and global positioning systems working in tandem to allow computers to automatically and safely operate motorized vehicles without human initiative. Autonomous vehicle (AV) technology has made great progress in the past few years. The application of AVs would reduce traffic accidents [8–10], alleviate traffic congestion [11,12], improve fuel economy [13–15], and reduce carbon emissions [16,17]. It would also improve the mobility of the elderly and the disabled [18], reduce the travel pressure on drivers [19], and improve the efficiency of multi-task work [20]. Therefore, shared AVs have the potential to solve the problem of deciding on a transportation method for the last mile of metro trips.

Although there is much in the literature regarding the impact of shared AVs on travel behavior, most studies mainly focus on the impacts of vehicle travel mileage [21–24], travel mode choice [25–28], and vehicle travel time [29,30]. Few studies have explored the use of shared AVs to solve the last-mile problem. In addition, most of the studies in the literature detail the influence of an individual's attitude and perception towards AVs and other latent psychological variables on the behavioral intention of choosing AVs. However, a mature theoretical framework that combines behavior with attitude [31], such as a combination of the technology acceptance model and the theory of planned behavior, has not been adopted.

In order to fill these gaps, we studied the latent psychological variables of travelers toward AVs in this paper, based on the mature theory of planned behavior, including attitudes (ATTs), subjective norms (SNs), perceived behavior control (PBC), and behavioral intention of use (BIU). Then, these variables were incorporated into the discrete choice model to establish a hybrid model, with Wuhan as an example, to conduct an empirical analysis of the influencing factors and degrees of influence of the last-mile travel mode choice behavior of travelers taking metro trips (beginning and ending in the city). The results of this paper are expected to improve the service level of the metro and provide insights for transportation planning within 1.5 km of subway stations. The main contributions of this paper are listed as follows:

(1) There was significant heterogeneity for travelers in their travel mode choices for the last mile of metro trips. (2) Respondents' latent psychological variables towards AVs had significant impacts on their travel behavior, but the impacts varied among different segments. (3) Demographic characteristics, such as education, career, and monthly household income, had a significant impact on the membership of each latent class (LC). (4) The willingness to pay for walking and waiting times, as well as in-vehicle time, varied significantly among travelers in different segments. (5) Elastic analysis results illustrated that a 1% increase in the travel cost for shared AVs in segment 1 led to a 7.598% decrease in the probability of choosing shared AVs.

The paper is structured as follows: Section 2 presents the literature review. In Section 3, the structural equation models (SEMs) and LC choice models are briefly discussed. Section 4 presents the survey design, data collection process, and descriptive statistics. Section 5 shows and discusses the results of the final estimated model. Finally, conclusions and recommendations for further research are presented in Section 6. An AV, in this paper, refers to a fully self-driving vehicle.

2. Literature Review

Travel time and travel costs are considered the most critical factors affecting travel behavior. Ortúzar [32] investigated travel mode choice in the Garforth Corridor in West Yorkshire, England, and found that in-vehicle time, out-of-vehicle time, and travel costs were significant factors affecting travelers' travel mode choices. Stern [33] asserted that travel cost was related to travel mode choice for elderly and disabled people in rural Virginia. Ewing et al. [34] confirmed that travel time significantly influenced the school travel mode choices of students in Gainesville, Florida. Frank et al. [35] explored factors affecting the travel mode choices and trip-chaining patterns of residents in the Central Puget Sound (Seattle) region and ascertained that travel time and cost significantly affected travel behavior. Wang et al. [36] believed that travel cost determines the use of shared travel modes in Beijing.

Sociodemographic factors also have a substantial impact on travel behavior. Schwanen et al. [37] confirmed that the contributory factors of travel mode choices for senior citizens taking leisure trips included age, gender, car ownership, possession of a driver's license, and educational attainment. Zhang [38] analyzed the travel mode choices of travelers in Metropolitan Boston and Hong Kong and found that their choices were affected by socioeconomic characteristics, such as age, job, homeownership, children, and car availability. Verplanken et al. [39] believed that the travel mode choices of university employees were related to age and gender. Tilahun et al. [40] explored the travel mode choices of commuters in the northeastern Illinois area and demonstrated that their choices were effected by gender, age, vehicle/household size, income, and vehicle availability.

Besides travel time, travel costs, and socioeconomic characteristics, the latent psychological variables, such as values, norms, ATTs, perceptions, and desire, play a pivotal role in an individual's travel mode choice [39,41,42]. Numerous studies have delved into individuals' attitudes and perceptions regarding autonomous vehicles (AVs). For instance, Sanbonmatsu et al. [43] found that an individual with a higher awareness of AVs has a stronger intention to use them. Panagiotopoulos et al. [44] asserted that latent variables such as perceived usefulness, perceived ease to use, perceived trust, and social influence, significantly impact respondents' behavioral intentions towards AV usage. Choi et al. [45] and Kaur et al. [46] concluded that perceived trust positively affects the adoption of AVs. Haboucha et al. [47] stated that pro-AV sentiments, environmental concern, and technology interest are related to users' preferences regarding AVs. Lavieri et al. [48] suggested that privacy sensitivity is related to individuals' willingness to share trips with strangers. Nevertheless, most studies have not adopted a mature theoretical framework that combines behavior with attitude [31], such as the technology acceptance model and theory of planned behavior.

Discrete choice models have been widely used to study individual travel behavior. The multinomial logit (MNL) model is the most common in practical applications due to fewer sample requirements, mature technology, and easy implementation [49]. However, the MNL model is not without limitations. Specifically, it assumes uniform preferences across individuals and upholds the principle of independence of irrelevant alternatives (IIA). When alternatives are inherently independent, the IIA assumptions may not align with real-world scenarios, leading to issues exemplified by the "red bus or blue bus" problem [50,51]. The nested logit (NL) model came into being in response to the flaw of IIA. The NL model establishes a tree structure based on the correlation between the alternatives: the alternatives are dependent on the same nest but independent among different nests, which overcomes the IIA problem to a certain extent [32]. The significant challenge in employing the NL model is to determine the tree structure reasonably [52]. Unlike the fixed coefficients in the MNL model, the mixed logit (ML) model assumes that the coefficients of the explanatory variables are random and obey a specific probability distribution. Therefore, the ML model can solve the preference heterogeneity problem [53,54]. The ML model can also be called the random parameter logit (RPL) model. The ML model needs to determine the distribution type that the model coefficients obey in advance, and then the corresponding parameter values can be estimated [55]. Typical parameter values are the mean and standard deviation. The former reflects the average preference, while the latter is the magnitude of the preference difference. Like the ML model, the latent class (LC) model handles the problem of random preference heterogeneity by dividing the respondents into several classes and applying different coefficients, respectively [56]. Although both LC and ML models serve as primary instruments for navigating preference heterogeneity, empirical studies often indicate a slight superiority of the LC model over the ML in aspects such as goodness of fit, theoretical foundation, and information depth [57,58]. Based on the above discussion, this study aims to analyze the effects of travel time, travel cost, socioeconomic characteristics, and psychological latent variables on autonomous vehicles to solve the last-mile problem of metro trips.

3. Methodology

In this section, we delineate the construction of the structural equation model (SEM) and latent class choice model (LCCM).

3.1. Structural Equation Models

Structural equation modeling (SEM) is a statistical data method used to explore the relationship between latent and observable variables and the internal relationship between latent variables. An SEM is developed to analyze the respondent's behavioral intentions to use AVs, and then the latent variables are incorporated into the LCCM to build a hybrid logit model.

The SEM contains a measurement equation and a structural equation. The measurement equation is established to describe the relationship between latent variables and observed variables expressed in a Likert scale. The structural equation is applied to describe the internal relationship between latent variables.

The expression of the measurement model and structural model is presented as follows:

$$\boldsymbol{X} = \boldsymbol{\Lambda}_X \boldsymbol{\xi} + \boldsymbol{\delta}_X \tag{1}$$

where $\boldsymbol{X}$ is a vector of exogenous observed variables, $\boldsymbol{\xi}$ is a vector of exogenous latent variables, $\boldsymbol{\Lambda}_X$ is a factor loading matrix of $\boldsymbol{X}$ in $\boldsymbol{\xi}$, and $\boldsymbol{\delta}_X$ is an error vector.

$$\boldsymbol{Y} = \boldsymbol{\Lambda}_Y \boldsymbol{\eta} + \boldsymbol{\delta}_Y \tag{2}$$

where $\boldsymbol{Y}$ is a vector of endogenous variables, $\boldsymbol{\eta}$ is a vector of endogenous latent variables, $\boldsymbol{\Lambda}_Y$ is a factor loading matrix of $\boldsymbol{Y}$ in $\boldsymbol{\eta}$, and $\boldsymbol{\delta}_Y$ is an error vector.

$$\boldsymbol{\eta} = \boldsymbol{B}\boldsymbol{\eta} + \boldsymbol{\Gamma}\boldsymbol{\zeta} + \boldsymbol{\delta}_{\eta} \tag{3}$$

where $\boldsymbol{B}$ is a coefficient matrix that describes the interaction between the endogenous latent variables, $\boldsymbol{\Gamma}$ is a coefficient matrix that describes the effects of exogenous latent variables on the endogenous latent variables, and $\boldsymbol{\delta}_{\eta}$ is a residual vector of the structural model.

Four latent variables are extracted to explore the respondents' acceptance towards AVs based on the theory of planned behavior. The latent variables, corresponding observed variables, and source of constructs are illustrated in Table 1.

Table 1. Latent variables, corresponding observed variables, and source of constructs.

Latent Variable	Observed Variable	Literature
Attitudes (ATTs)	ATT 1: For me, adopting an AV is unfavorable/favorable. ATT 2: For me, adopting an AV is negative/positive. ATT 3: For me, adopting an AV is undesirable/desirable.	[59,60]
Subjective norms (SNs)	SN1: Most people who are important to me would support that I take the KMRT to commute SN2: People who are important to me expect that I should use an AV in the future. SN3: If people around me use AVs, I will also use AVs.	[59–61]
Perceived behavioral control (PBC)	PBC1: Whether or not I use an AV when traveling is completely up to me. PBC2: I have enough resources (money) to use an AV when traveling. PBC3: I have enough opportunities to use an AV when traveling.	[59,62]
Behavioral intention to use (BIU)	BIU1: I intend to use FAD vehicles in the future. BIU2: I intend to buy FAD vehicles in the future. BIU3: I will recommend family members and friends to ride in FAD vehicles.	[45,63]

3.2. Latent Class Choice Model

The LC choice model calibrates the sample into C LCs/segments. Each class has a specific parameter vector, capturing and accommodating preference heterogeneity across individuals [56]. In this paper, we assumed an MNL model to estimate the choice probabilities within the class. The choice probability of individual i choosing alternative j among alternatives J in choice situation t within class c is shown in Equation (4).

$$P_{ij|c} = P(y_{it} = j|class = c) = \frac{exp(\beta_c x_{ijt})}{\sum_{j=1}^{J} exp(\beta_c x_{ijt})},\ c = 1, 2, \cdots, C \tag{4}$$

where x_{ijt} is the characteristic vector of alternative j among alternatives J in choice situation t, and β_c is the coefficient vector of x_{ijt} within the class c.

The class assignment membership is measured by the prior membership probability of individual i belonging to class c, which can be calculated by the function below:

$$Prob(class = c) = H_{ic} = \frac{exp(\theta_c z_i)}{\sum_{c=1}^{C} exp(\theta_c z_i)} \tag{5}$$

where z_i is an optional set of invariant characteristics such as demographic characteristics, which can be incorporated into a class membership probability function to analyze individual preference heterogeneity. θ_c is an unknown coefficient vector.

In the LC choice model, the LC c is unknown and needs to be assumed in advance. Usually, we set the number of LCs c to 2, and then increase the value of c sequentially until the optimal goodness of fit is reached. The optimal number of classes c can be estimated by the Bayesian information criterion (BIC) and consistent Akaike information criterion ($CAIC$) [64,65], as illustrated in Equations (6) and (7).

$$BIC = -2 \ln L + m \ln N \tag{6}$$

$$CAIC = -2 \ln L + m(1 + \ln N) \tag{7}$$

where ln$L$ is the maximized log-likelihood at the convergence, m is the number of estimated parameters, and N is the sample size. The value of C is selected when AIC and BIC are minimized.

4. Data

4.1. Survey Design

We conducted a survey to study the influence of shared AVs on metro trips' last-mile travel behavior, including three parts. The first part focuses on the socioeconomic characteristics of respondents, including gender, age, education level, household income level, career, household size, car ownership, and license.

The second part concentrates on respondents' ATTs based on the theory of planned behavior, which can influence individuals' preferences for AVs. Each respondent answered 12 statements to indicate their level of agreement with a five-point Likert scale ranging from strongly agree to strongly disagree. The statements explored respondents' psychological latent variables towards AVs, such as ATTs, SNs, PBC, and BIU. Three statements were provided for each latent variable to gain insight into the respondents' ATTs.

The third part consists in a series of stated preference questions. Every respondent was asked their intention to use four travel mode options, including walk, shared bike, bus, and shared AVs. Three scenarios with a last-mile travel distance of 500, 1000, and 1500 m were considered. The attributes of the alternatives considered in the SP experiments included in-vehicle time, walking and waiting time, and travel cost. All attributes and attribute levels for each alternative are shown in Table 2. We constructed a fractional factorial experimental design to generate choice sets for respondents rather than a full factorial design, which would cause a massive number of choice sets. The software package

JMP13 was applied to conduct efficient designs based on the D-efficiency criterion [66]. The D-efficient design aims to reduce the variance of the coefficients. The efficient designs generated four questionnaires, and each questionnaire contains six scenarios. Every respondent answered a questionnaire randomly and anonymously. An example of an SP choice scenario is presented in Figure 1 [66].

Table 2. Attributes and attribute levels for travel modes.

Travel Modes	Attributes	Attribute Levels
Walk	Travel time (min)	−30%; −10%; +20% of the calculated trip time (speed: 4 km/h)
Shared bike	Trip cost (CNY)	−30%; −10%; +20% of the estimated cost for the trip (CNY 1.5, less than 30 min; CNY 3, 31–60 min)
	In-vehicle time (min)	−30%; −10%; +20% of the calculated trip time (speed: 15 km/h)
Bus	Trip cost (CNY)	−30%; −10%; +20% of the trip cost (CNY 1,2)
	In-vehicle time (min)	−30%; −10%; +20% of the calculated trip time (speed: 18 km/h)
	Walking and waiting time (min)	4–7–10
Autonomous vehicle	Trip cost (CNY)	−30%; −10%; +20% of the estimated cost for the trip (CNY 2/500 m)
	In-vehicle time (min)	−30%; −10%; +20% of the calculated trip time (speed: 40 km/h)
	Walking and waiting time (min)	2–5–8

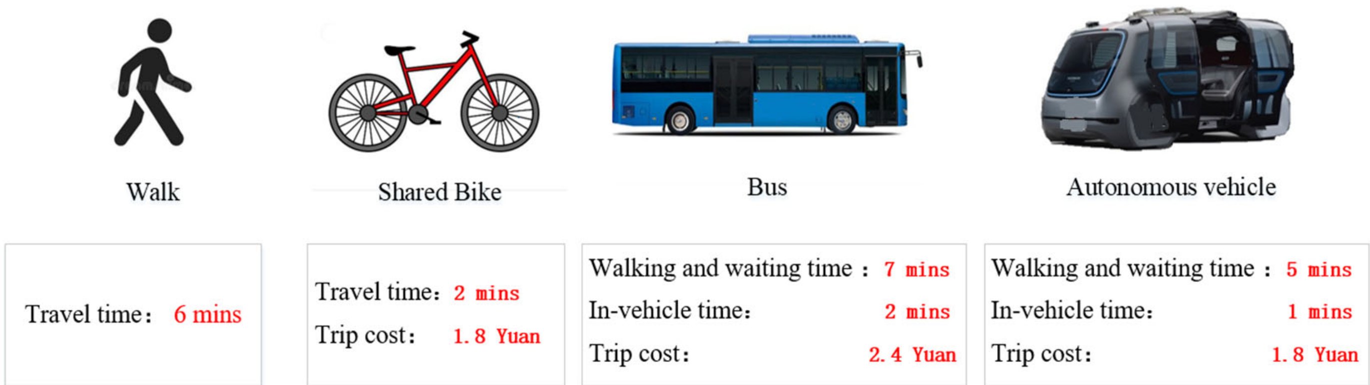

Figure 1. Example of SP choice scenario.

4.2. Data Collection and Descriptive Statistics

The survey consisted of a pre-test and formal investigation. The pre-test questionnaire in the first stage was conducted offline. The questionnaire was randomly distributed to 50 passers-by and then corrected based on the feedback and suggestions. In the second phase of the formal investigation, data collection was conducted in Wuhan using online and offline methods. The questionnaire was distributed from March to May 2021 and lasted for two months. A total of 676 valid samples were recovered in this survey, and 51 questionnaires were eliminated due to missing information. The demographic characteristics of the sample are shown in Table 3.

Table 3 shows that among all the respondents, 50.15% were female and 49.85% were male. Respondents aged 31–45 years accounted for 42.16%, followed by those aged 18–30 years, accounting for 38.31%. Respondents with bachelor's degrees were the most common, accounting for 44.38%. Enterprise employees had the highest proportion, accounting for 31.51%. Monthly household income of less than CNY 5000 accounted for 33.58%, CNY 5001 to 10,000 accounted for 32.40%, CNY 10,001 to 20,000 accounted for 18.93, and more than CNY 20,001 accounted for 15.09%. Furthermore, 50.15% of respondents had school-age children, 66.57% of respondents' families owned at least one car, 55.47% of respondents possessed driver licenses, and 84.62% of the respondents' families had at least three residents. Of 4056 scenarios, 37.01% chose walking, 37.99% chose shared bikes, 11.91% chose shared AVs, and 13.09% chose the bus.

Table 3. Demographic characteristics of the sample.

Category	Variable	Frequency	Percentage (%)
Gender	Male	337	49.85%
	Female	339	50.15%
Age (years)	18–30	259	38.31%
	31–45	285	42.16%
	46–55	109	16.12%
	More than 55	24	3.55%
Education	Secondary school and below	143	21.15%
	Associate's degree	179	26.48%
	Bachelor's degree	300	44.38%
	Master's degree and above	53	7.84%
Career	Public servant/Public institution	169	25.00%
	Enterprise employees	213	31.51%
	Self-employed/Freelance	192	28.40%
	Other	102	15.09%
Monthly household income (CNY)	Less than 5000	227	33.58%
	5001–10,000	219	32.40%
	10,001–20,000	128	18.93%
	More than 20,001	102	15.09%
School children	Yes	339	50.15%
	No	337	49.85%
Car ownership	Yes	450	66.57%
	No	226	33.43%
License	Yes	375	55.47%
	No	301	44.53%
Physical or electronic IC card	Yes	459	67.90%
	No	217	32.10%
Household size	One	26	3.85%
	Two	78	11.54%
	Three	238	35.21%
	Four	189	27.96%
	More than five	145	21.45%

5. Results

5.1. Results of Latent Variable Model

Stata 15.0 was used to test the latent variable model in the study. A confirmatory factor analysis (CFA) was conducted to ascertain the influence of variables on the adoption of AVs. The data needed to be evaluated for reliability and validity before performing CFA. Table 4 provides details of the reliability and convergent validity of constructs. Standardized factor loadings are a measure of the strength of the relationship between an observed variable and a latent variable, which indicates the degree of linear relationship that exists between an observed variable and the factor to which it belongs. The standardized factor loadings of 12 observed variables ranged from 0.851 to 0.961, exceeding the standard of 0.5 [67]. Cronbach's alpha is a measure of the reliability of a scale or test. All Cronbach's alpha values of four latent variables were above the acceptable level of 0.70 [68]. The composite reliability (CR) of a latent variable is the combination of the reliabilities of all its observed variables, and this indicator is used to analyze the consistency among the observed variables of the latent variable. The minimum CR value was 0.921, and all values were higher than the minimum threshold of 0.7 [69]. The average variance extracted (AVE) calculates the variance explanatory power of the latent variable, i.e., it directly shows how much of the variance explained by the latent variable is from measurement error. The AVE values of all constructs were between 0.797 and 0.893, indicating that the measurement model has a good structural reliability and convergence validity [69]. Table 5 presents the results from the discriminant validity examination. All square values of AVE are higher than the inter-construct correlations, demonstrating that the latent variables have acceptable discriminant validity. The measurement model has been validated and used for structural model analysis.

Table 4. Reliability and convergent validity of constructs.

Latent Variable	Observed Variable	Means	SD	Standardized Factor Loading	Cronbach's α	CR	AVE
Attitudes (ATTs)	ATT1	3.571	1.076	0.947	0.940	0.962	0.893
	ATT2	3.572	1.052	0.949			
	ATT3	3.641	1.086	0.939			
Subjective norms (SNs)	SN1	3.478	1.093	0.940	0.929	0.955	0.876
	SN2	3.507	1.078	0.943			
	SN3	3.550	1.079	0.924			
Perceived behavioral control (PBC)	PBC1	3.695	1.083	0.851	0.872	0.921	0.797
	PBC2	3.456	1.114	0.920			
	PBC3	3.410	1.13	0.905			
Behavioral intention to use (BIU)	BIU1	3.513	1.052	0.941	0.941	0.962	0.893
	BIU2	3.510	1.041	0.961			
	BIU3	3.425	1.087	0.933			

Table 5. Results of discriminant validity test.

Latent Variable	ATTs	SNs	PBC	BIU
ATTs	**0.945**			
SNs	0.737	**0.936**		
PBC	0.668	0.688	**0.893**	
BIU	0.693	0.69	0.659	**0.945**

Note: Values along diagonal (in bold) are the square values of the constructs. Values below diagonal are the correlations between two constructs.

The estimation results of latent variable measurement and SEMs indicated that the model fits the data well based on fit indices such as chi-square/degree of freedom (χ^2/df), the root mean squared error of approximation (RMSEA), the comparative fit index (CFI), the Tucker–Lewis index (TLI), and standardized root mean square residual (SRMR). The chi-square/degree of freedom is a hypothesis testing method used in data analysis to detect the relationship between two categorical variables. The root mean squared error of approximation is an index that evaluates the model's lack of fit; if it is close to 0 it indicates a good fit, and conversely, the further away from 0 the worse the fit. The comparative fit index is obtained when comparing a hypothetical model with an independent model. Its value ranges from 0 to 1, with a value closer to 0 indicating a worse fit and closer to 1 indicating a better fit. The Tucker–Lewis index is a comparative fit index that takes values between 0 and 1, with a value closer to 0 indicating a worse fit and closer to 1 indicating a better fit. The standardized root mean square residual is an absolute goodness-of-fit index, which is used to assess the average size of the difference between the observed and expected correlation matrices. χ^2/df = 3.775 (critical value is between 1 and 5 when the sample size exceeds 500 according to [60]), RMSEA = 0.064 (less than the critical value of 0.08 based on [70]), CFI = 0.983 (more than the critical value of 0.90 on the basis of [71]), TLI = 0.977 (more than the critical value of 0.90 in accordance with [68]), SRMR = 0.024 (less than the critical value of 0.08 on the basis of [72]).

5.2. Results of Latent Class Choice Model

In principle, more classes mean better goodness of fit at the cost of decreasing parsimony. The Bayesian information criterion (*BIC*) is a widely recognized statistical method employed for choosing the most appropriate model from a defined set of candidates. It computes the probability function and adds a penalty term for the number of parameters in the model. The consistent Akaike information criterion (*CAIC*) is an adapted form of the classic Akaike information criterion, which was developed by modifying penalties. This helps to avoid overfitting and provides a balanced approach to model selection. Both *BIC* and *CAIC* were proposed to penalize the number of classes. Table 6 summarizes these measures concerning the models with one to six classes. Among them, the four-segment LC model has the lowest *BIC* and *CAIC*, and the rho-bar squared between 4 and 5 is 0.0009. Four classes might be the optimal number of classes considering the objective of the study and its simplicity. As shown in Table 7, all models with LCs outperform the single-segment model (MNL model), confirming the heterogeneity of the preferences of the sample.

Table 6. Summary statistics of estimated models.

Number of Segments	Number of Parameters	Log-Likelihood	AIC	*CAIC*	*BIC*	Rho-Bar Squared
1	7	−4998.59	10,011.2	10,011.2	10,055.3	0.0181
2	23	−4182.18	8410.6	8410.4	8555.4	0.2548
3	39	−3615.08	7308.9	7308.2	7554.2	0.3550
4	55	−3360.26	6832.1	6830.5	7177.4	0.3997
5	71	−3350.60	6845.8	6843.2	7291.1	0.4006

Table 7. Estimation results of multinomial and four-segment latent class models.

Parameter	MNL Model		Four-Segment LC Model							
			Segment 1		Segment 2		Segment 3		Segment 4	
	Coefficient	Z Value	Coefficient	Z Value	Coefficient	Z Value	Coefficient	Z Value	Coefficient	Z Value
Walking and waiting time (min)	−0.143 ***	−21.31	−0.462 ***	−3.85	−0.028 ***	−3.1	−3.002 ***	−4.78	0.773 ***	3.54
In-vehicle time (min)	−0.027 ***	−6.13	0.016	0.52	−0.052 ***	−6.3	−0.429 ***	−8.07	−1.024	−0.77
Trip cost (CNY)	−0.201 ***	−9.69	−1.910 ***	−7.92	−0.154 ***	−5.05	−0.408 **	−2.18	−0.514	−0.67
ATT	0.407 ***	4.47	−4.252 ***	−6.34	0.133	1.42	2.333	1.61	72.574 **	2.18
SN	0.293 ***	3.25	2.263 *	1.89	−0.042	−0.47	−0.047	−0.04	−61.177 **	−1.99
PBC	−0.039	−0.41	−0.056	−0.04	0.082	0.74	−4.828 ***	−2.66	11.158 **	2.09
BIU	0.232 ***	2.88	2.830 ***	2.94	−0.006	−0.06	3.724 **	2.54	1.731	0.55
Model statistics										
Segment size/membership			0.287		0.378		0.262		0.073	
Number of respondents	676									
Log-likelihood	−4998.586		−3360.256							
Rho-bar squared	0.018		0.400							

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

The chosen four-segment model exhibits a rho-bar squared value of 0.400. The class probability model includes socioeconomic characteristics as explanatory variables, and the parameters are shown in Table 8. Table 7 presents the model statistics of multinomial and four-segment LC models. Notably, segment 4 comprises only 7.3% of the overall sample. Within this segment, the coefficients for walking and waiting time are significantly positive, whereas those for in-vehicle time and trip cost prove to be statistically inconsequential. This indicates that respondents within this segment may not have fully grasped the essence of the choice task presented to them.

Segment 1 comprises 28.7% of the total sample. The parameter estimates and corresponding z values in segment 1 indicate that both walking and waiting time and trip cost are statistically significant, suggesting that increasing walking and waiting time and travel cost will reduce travelers' willingness to use a certain travel mode. A significant majority of respondents favored walking (93.9%), while a comparatively smaller portion preferred shared bikes (4.8%). The results indicate that segment 1 is interested in walking. According to the class member model, respondents who belonged to segment 1 are more likely to possess bachelor's degrees and upper middle income (CNY 10,001–20,000 monthly) and are less likely to have education levels of secondary school and below. Furthermore, the latent psychological variables such as ATT and BIU are related to the total utility for using AVs. The ATT towards AVs has a strongly negative contribution (marginal value equals −4.251) to the total utility of using AVs as last-mile transport. The results show that respondents who are positive about adopting AVs are less willing to use AVs as egress mode. The latent psychological variable BIU contributes positively to the total utility, indicating that a higher BIU decreases the disutility of using AVs for last-mile trips.

Table 8. Estimation results of the class probability model.

Variables	Segment 1		Segment 2		Segment 3		Segment 4	
	Coefficient	Z Value	Coefficient	Z Value	Coefficient	Z Value	Coefficient	Z Value
Intercept	1.275 ***	0.321	1.853 ***	0.307	1.049 ***	0.333	0	
Secondary school and below	−0.856 **	0.423	−1.421 ***	0.435	−0.635	0.430	0	
Associate's degree	−0.072	0.448	0.796 *	0.427	−0.572	0.491	0	
Bachelor's degree	0.830 ***	0.318	1.152 ***	0.325	0.689 **	0.329	0	
Public servant/Public institution	0.388	0.450	0.845 **	0.427	−0.038	0.470	0	
Enterprise employees	−0.159	0.462	0.892 **	0.426	0.040	0.477	0	
Less than CNY 5000	0.201	0.382	0.687 *	0.384	0.148	0.385	0	
CNY 10,001–20,000	1.068 *	0.549	1.279 **	0.551	1.450 ***	0.550	0	

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Segment 2 consists of 37.8% of the respondents. Within this segment, the transportation mode preferences are distributed as follows: walking (21.8%), shared bikes (33.5%), shared AVs (16.2%), and buses (28.4%). Demographically, individuals in this segment predominantly possess a bachelor's degree and are employed as public servants, in public institutions, or within enterprises. Their income levels tend to be median when compared to other segments. The parameter estimates of travel characteristics are all statistically significant. However, none of the latent psychological variables regarding AVs influence travelers' preference for AVs as egress mode in segment 2. This observation suggests that respondents in segment 2 are not familiar with AVs.

Segment 3 includes 26.2% of the overall sample. A striking majority of these respondents, 91.3%, favor shared bikes, indicating a dominant inclination towards this mode of transportation for last-mile journeys within this group. In terms of socioeconomic characteristics, individuals in this segment are more likely to possess a bachelor's degree in the upper-middle-income category, demonstrating that shared bikes are attractive for these travelers in the last mile trip. The waiting and walking time, in-vehicle time, and travel cost proved statistically significant. BIU has a significant positive influence, while PBC has a significant negative effect on the utility function of choosing AVs for last-mile transport.

5.3. Elasticities

Table 9 presents both the direct and cross-elasticities related to the travel cost for each of the travel modes, aiming to analyze the variation in preferences among the three latent classes (LCs), excluding the residual segment 4. The elasticities illustrate the percentage change in the choice probability of four travel modes due to a 1% change in the level of travel cost. For example, a 1% increase in the travel cost for shared AVs leads to a 0.649% decrease in the choice probability of shared AVs (i.e., direct elasticity), while it causes a 0.105% increase in the probability of choosing walking, shared bikes, and buses (i.e., cross-elasticity) when considering the entire sample. The direct elasticities of travel cost for all travel modes of the MNL model and class2 were bigger than negative 1, showing that a 1% increase in the travel cost for all travel modes will decrease choice probabilities by less than 1%. However, the direct elasticities of travel cost for all travel modes of class1 are smaller than negative 1 and those in the MNL model, class2, and class3, which indicates that respondents from class1 are more sensitive to travel cost than individuals from class2 and class3. In class1, a 1% increase in the travel cost for shared AVs leads to a 7.598% decrease in the choice probability of shared AVs.

Table 9. Elasticities and cross-elasticities of travel cost (CNY).

Model		Transport Mode	Walk	Shared Bike	Shared AV	Bus
MNL model	All sample	Walk	0	0	0	0
		Shared bike	0.103	−0.186	0.103	0.103
		Shared AV	0.105	0.105	−0.649	0.105
		Bus	0.046	0.046	0.046	−0.320
Four-class LC model	Segment 1	Walk	0	0	0	0
		Shared bike	0.146	−2.795	0.146	0.146
		Shared AV	0.070	0.070	−7.598	0.070
		Bus	0.013	0.013	0.013	−3.650
	Segment 2	Walk	0	0	0	0
		Shared bike	0.119	−0.269	0.119	0.119
		Shared AV	0.180	0.180	−0.808	0.180
		Bus	0.132	0.132	0.132	−0.374
	Segment 3	Walk	0	0	0	0
		Shared bike	0.472	−0.045	0.472	0.472
		Shared AV	0.005	0.005	−1.335	0.005
		Bus	0.000	0.000	0.000	−0.644

5.4. Willingness to Pay

Although travelers from different segments have the same signs for preferences, there are differences in sensitivities to walking and waiting time, in-vehicle time, and trip cost. The travelers' willingness to pay is calculated as a trade-off ratio between the estimated time parameter and the estimated cost parameter. Table 10 shows travelers' willingness to pay values across distinct segments. Individuals from segment 1 who are sensitive to travel costs were willing to pay CNY 14.5 to reduce a one-hour walking and waiting time. In-vehicle time was found to have an insignificant influence on respondents' last-mile egress mode. Conversely, travelers in segment 3 were willing to pay up to CNY 441.3 and CNY 63.0 to decrease one-hour walking and waiting time and in-vehicle time. The results are consistent with previous research. Seelhorst and Liu (2015) postulated that price-sensitive travelers were willing to pay less to reduce travel time [73]. Wen and Lai (2010) discovered that travelers with high incomes were willing to pay more to improve service quality [74].

Table 10. Willingness to pay (CNY/per hour) for each of the segments.

Variables	Four-Segment LC Model			
	Segment 1	Segment 2	Segment 3	Segment 4
Walking and waiting time	14.5	11.0	441.3	-
In-vehicle time	-	20.4	63.0	-

6. Discussion

6.1. Summary of Results

This study positioned shared AVs in the public transport market and applied an LC model to understand the unobserved preference heterogeneity across respondents. Four distinct market segments concerning the preference were identified for the last-mile travel mode choice of metro trips. By analyzing the preference heterogeneity and group characteristics of these LCs, we can determine the target group for using shared AVs in the last mile of metro trips. Travelers who choose shared AVs with the highest proportion belong to segment 2. These people are more likely to possess a bachelor's degree, work in public servants/public institutions, and be enterprise employees with a middle income. Different strategies should be used to increase the attractiveness of shared AVs in response to the heterogeneity of choice preferences of travelers from different segments.

Latent psychological variables exerted differential impacts across segments. The latent psychological variables of attitude towards AVs have a significant negative impact on the trips of travelers from segment 1 while they have positive effect on the travelers from segment 4, indicating that travelers from segment 1 lack sufficient knowledge of AVs. In the process of promoting and popularizing AVs, it is important to consider the psychological attitudes of travelers towards AVs. The direct elasticity analysis shows that the travelers from segment 1 are most sensitive to travel costs, and the direct elasticity value reaches −7.598, which indicates that a 1% increase in the travel cost for shared AVs leads to a 7.598% decrease in the choice probability of shared AVs. The cross-elasticity analysis shows that the cost of shared bicycles has the greatest impact on shared AVs. In segment 3, a 1% increase in the travel cost for shared bikes will cause a 0.472% increase in the choice probability of shared AVs. This suggests that an astutely calibrated pricing strategy can facilitate the promotion and adoption of shared AVs.

Travelers from different segments have different willingness to pay for walking and waiting time and in-vehicle time. For travelers from segment 1, in-vehicle time does not significantly influence their willingness to pay. Conversely, those from segment 2 are willing to pay CNY 20.4 to reduce one-hour in-vehicle time, while for segment 3, this value rises to CNY 60.3 per hour. Walking and waiting times significantly impact travelers from all segments, but the magnitude of the impact varies greatly. Travelers from segment 2 are willing to pay CNY 11.0 to reduce one-hour walking and waiting time, while segment 3 travelers are willing to pay up to CNY 441.3 for the same reduction. The results show that the value of travel time for high-income groups is relatively higher. Hence, the travel experience of travelers can be improved by rationally designing the operation routes and departure intervals of shared AVs to reduce the walking and waiting time.

6.2. Contributions and Comparison to Literature

The contribution of this paper mainly includes three aspects. From the perspective of research objects, although Chinese AVs have made rapid progress, there is no research on Chinese shared AVs to solve the problem of the last mile of metro trips. Although AVs have been studied in the Netherlands, Atlanta area, Ann Arbor–Detroit Area, and other areas [3,4,75], findings from these areas may not be applicable to other areas.

From the perspective of research methods, diverging from prevailing methodologies that deploy cluster analysis to discern user groups [76], this paper is the first time that the LC logit model has been used to study travelers' preferences to choose shared AVs to solve the last-mile problem of metro trips.

From the perspective of influencing factors, in addition to socioeconomic attributes and travel characteristic variables that have an impact on travel behavior, travelers' psychological latent variables have a significant impact on travel mode choice. For example, the perceived trust and perceived reliability of AVs affect travelers' preference for AVs [3]. Nevertheless, few studies focused on mature theoretical frameworks that combine behavior and attitude [31]. Addressing this gap, this paper adopts the theory of planned behavior to study latent psychological variables, including ATTs, SNs, PBC, and BIU of travelers towards AVs.

6.3. Limitations and Further Work

This area still needs to be further studied. Firstly, the results of this paper are mainly specific to the research area. Research results in different countries and regions will vary. Secondly, the COVID-19 pandemic has markedly reshaped travel behaviors worldwide. Future research can consider the impact of COVID-19 on travelers' preference for shared AVs. Thirdly, this paper mainly studies the option of metro and transfer while ignoring the option of private AVs throughout the journey. More options for travel indicate a more complex system and greater uncertainty. Studying more modes of travel helps to understand this uncertainty. Finally, this paper does not fully consider the influence of distinct geographic and regional characteristics on travel behaviors. For instance, the impact of significant landmarks such as the Yangtze River on residents' travel behaviors or the discrepancies in travel mode choices between primary urban areas and their peripheral counterparts warrants attention in future studies.

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