Article

Not peer-reviewed version

Shared Autonomous Vehicles as Last Mile Public Transport of Multimodal Train Trips

Zhiwei Liu * and Jianrong Liu

Posted Date: 29 August 2023

doi: 10.20944/preprints202308.1939.v1

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

Article

Shared Autonomous Vehicles as Last Mile Public Transport of Multimodal Train Trips

Zhiwei Liu [1,*] and Jianrong Liu [2]

[1] School of Civil Engineering and Architecture, Wuhan Polytechnic University, Wuhan City, China; tonyliuzhiwei@whpu.edu.cn

[2] School of Civil Engineering and Transportation, South China University of Technology, Guangzhou City, China; ctjrliu@scut.edu.cn

* Correspondence: tonyliuzhiwei@whpu.edu.cn; Tel.: (86)17786114447; Science and Education Building 1208, 68 Xuefu South Road, Changqing Garden, Wuhan, China, Zip Code: 430023

Abstract: The accessibility of public transportation is also known as the last mile problem, and it is one of the main obstacles that affect travelers to choose 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 train trips' last-mile travel behavior 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 the latent psychological variables, including travelers' attitudes (ATTs), subjective norms (SNs), perceived behavior control (PBC), and behavioral intention to use (BIU) toward AVs. These latent psychological variables are incorporated into the latent class (LC) logit model to establish a hybrid model to study the factors and degree of influence on the travel mode choice for the last mile of train trips. The results show that travelers have preference heterogeneity for the travel mode choice of the last mile of train 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 AV in segment 1 leads to a 7.598% decrease in the choice probability of shared AV. Respondents from different segments vary significantly in their willingness to pay, 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

---

1. Introduction

With the rapid and excessive development of motorization, most cities worldwide are confronted with traffic congestion, air deterioration, noise pollution, fossil energy consumption, carbon emissions [1]. Public transport, especially the train, has excellent advantages in alleviating traffic congestion, reducing fossil energy consumption, improving transportation efficiency, and reducing carbon emissions [2]. However, unlike private cars, the train 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 common last-mile travel modes include walking, shared bicycles, and buses. However, each mode has its advantages and disadvantages. For example, walking has excellent flexibility, economy, and environment-friendliness, and it benefits physical and mental health [5,6]. However, walking is only suitable for travel within 10 minutes [7], and its use is restricted in bad weather (e.g., rain and snow). Shared bicycles solve the problem of access and parking but are likely to cause traffic accidents and traffic congestion[1]. Similar to walking, shared bicycles are restricted in bad weather. The bus has the advantages of short travel time and low travel cost, but the walking and waiting time are relatively long, and the attractiveness is not enough.

 doi:10.20944/preprints202308.1939.v1

Autonomous vehicle (AV) technology has made great progress in the past few years. The application of AVs will reduce traffic accidents [8–10], alleviate traffic congestion [11,12], improve fuel economy [13–15], and reduce carbon emissions [16,17]. It will also improve the mobility of the elderly and the disabled [18], reduce the travel pressure of drivers [19], and improve the efficiency of multi-task work [20]. Therefore, shared AVs have the potential to solve the problem of the last mile of train trips.

Although there is much literature on the impact of shared AVs on travel behavior, most studies mainly focus on the impact 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 problem of the last mile of train trips. In addition, most of the literature studies the influence of an individual's attitude and perception towards AVs and other psychological latent variables on the behavioral intention of choosing AVs. However, a mature theoretical framework that combines behavior with attitude [31], such as the technology acceptance model and theory of planned behavior, has not been adopted.

In order to fill these gaps, this paper studies latent psychological variables of travelers toward AVs based on the mature theory of planned behavior, including attitudes (ATTs), subjective norms (SNs), perceived behavior control (PBC), and behavioral intention to use (BIU). Then, these variables are 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 degree of influence of the last-mile travel mode choice behavior of train trips. The results of this paper are expected to improve the service level of the train and provide insights for transportation planning within 1.5 kilometers of subway stations. The main contributions of this paper are listed as follows:

(1) There was a huge heterogeneity of travellers in the travel mode choice of the last mile of train trips; (2) Respondents' latent psychological variables towards AVs had a significant impact on their travel behaviour, but the impacts vary 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 time. in-vehicle time varied significantly among travellers from different segments; (5) Elastic analysis results illustrated that a 1% increase in the travel cost for shared AV in segment 1 leads to a 7.598% decrease in the choice probability of shared AV.

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 shortly discussed. Section 4 presents survey design, data collection, and descriptive statistics. Section 5 shows and discusses the results of the final estimated model. At last, 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] applied multinomial logit (MNL) and nested logit (NL) models to investigate travel mode choice in urban corridors and found that in-vehicle time, out-of-vehicle time, and travel costs were significant factors affecting travelers' mode choice in the Garforth Corridor in West Yorkshire, England. Stern [33] proposed a correlated MNL model and a Poisson regression model to determine the travel mode choice of elderly and disabled people in rural Virginia and demonstrated that travel cost is related to travel mode. Ewing et al. [34] confirmed that travel time significantly influenced the school travel mode choice of students in Gainesville, Florida. Frank et al. [35] established a discrete choice model to explore factors affecting the mode choice and trip chaining patterns of residents in the Central Puget Sound (Seattle) region and ascertained that travel time and cost significantly affect travel behavior. Wang et al. [36] believed that travel cost determines the travel mode share in Beijing using an NL model. Travelers' socioeconomic characteristics are also thought to influence travel mode choice significantly. Schwanen et al. [37] confirmed that contributory factors of travel mode choice of senior citizens for leisure trips include age, gender, car ownership, driver's license, and educational attainment. Zhang [38] analyzed the travel mode choice of travelers in Metropolitan Boston and Hong Kong and found that their choices are affected by socioeconomic characteristics, such as age, job, homeownership, children, and car availability. Verplanken et al. [39] believed that the travel mode choice of university employees is related to age and gender. Tilahun et al. [40] developed a discrete choice model to explore travel mode choice of commuters in the North-Eastern Illinois area and demonstrated that the choice is 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, are integral to an individual's travel mode choice [39,41,42]. Many studies explored individuals' opinions and ATTs regarding BIU AVs. Sanbonmatsu et al. [43] found that an individual with a higher awareness of AVs has a stronger intention to use the AV. Panagiotopoulos et al. [44] included that latent variables, such as perceived usefulness, perceived ease to use, perceived trust, and social influence, influence the respondents' behavioral intentions to use AVs. 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 has not adopted a mature theoretical framework that combines behavior with attitude [31], such as the technology acceptance model and theory of planned behavior.

The discrete choice model has been widely used to study individual travel behavior. The MNL model is the most common in practical applications due to fewer sample requirements, mature technology, and easy implementation [49]. Nevertheless, the MNL models have pronounced shortcomings. The model assumes homogenous preferences across different individuals and independence of irrelevant alternatives. If alternatives are independent, the IIA characteristics are not consistent with the actual situation, which may easily lead to the problem of red bus or blue bus [50,51]. The 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 difficulty of NL modeling 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 LC model handles the problem of random preference heterogeneity by dividing the respondents into several classes and applying different coefficients, respectively [56]. As the two primary tools for dealing with preference heterogeneity, the LC and the ML models have relatively similar results. However, most studies show that the LC model is slightly better than the ML model in terms of goodness of fit, theoretical basis, and information richness [57,58].

3. Methodology

This section introduces the formation of SEMs and LC choice models (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.

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:

$$X = \Lambda_X \xi + \delta_X \tag{1}$$

Where X is a vector of exogenous observed variables, ξ is a vector of exogenous latent variables, Λ_X is a factor loading matrix of X in ξ, and δ_X is an error vector.

$$Y = \Lambda_Y \eta + \delta_Y \tag{2}$$

Where Y is a vector of endogenous variables, η is a vector of endogenous latent variables, Λ_Y is a factor loading matrix of Y in η, and δ_Y is an error vector.

$$\eta = B\eta + \Gamma\zeta + \delta_\eta \tag{3}$$

Where B is a coefficient matrix that describes the interaction between the endogenous latent variables, Γ is a coefficient matrix that describes the effects of exogenous latent variables on the endogenous latent variables, and δ_η is a residual vector of the structural model.

Four latent variables are extracted to explore the respondents' ATTs 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 individual i choose alternative j among alternatives J in choice situation t within class c is shown in Eq. (4).

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

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.

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 29 August 2023 doi:10.20944/preprints202308.1939.v1

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 (Greene and Hensher, 2003):

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

Where z_i is an optional set of invariant characteristics such as demographic characteristics, which can be incorporated into 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 Bayesian information criterion (BIC) and consistent Akaike information criterion (CAIC) [64,65], as illustrated in Eqs. (6) and (7).

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

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

Where lnL 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

The second part focuses on the socioeconomic characteristics of respondents, including gender, age, education level, household income level, career, household size, car ownership, and license.

The third 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 disagree strongly. 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 get insight into the respondents' ATTs.

The last part engages in a series of stated preference questions. Every respondent was asked his 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 meters 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 JMP 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].

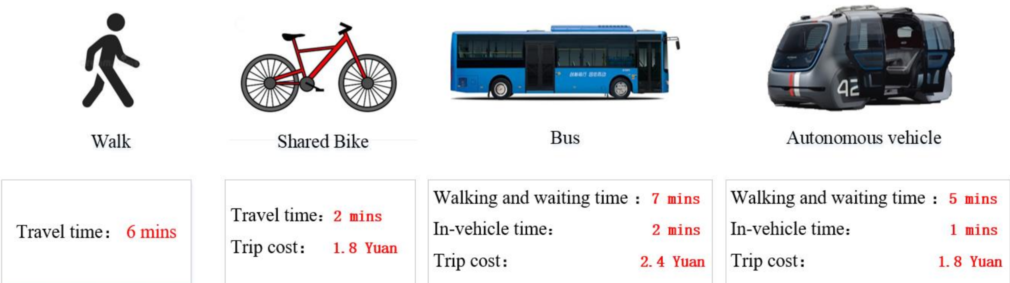

Figure 1. Example of SP choice scenario.

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 29 August 2023 doi:10.20944/preprints202308.1939.v1

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 (1.5 CNY, less than 30 min; 3 CNY, 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 (1,2 CNY)
	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 (2 CNY/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

4.2. Data collection and descriptive statistics

The survey consisted of 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 SP survey 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. 31-45 years old occupied 42.16%, followed by 18-30 years old, accounting for 38.31%. Bachelor's degrees made up the greatest number, accounting for 44.38%. Enterprise employees had the highest proportion, accounting for 31.51%. Monthly household income of less than 5000 CNY accounted for 33.58%, 5001 to 10000 CNY accounted for 32.40%, 10001 to 20000 CNY accounted for 18.93, and more than 20001 CNY 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 walk, 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 degree	179	26.48%
	Bachelor degree	300	44.38%
	Master 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%

 doi:10.20944/preprints202308.1939.v1

	5001-10000	219	32.40%
	10001-20000	128	18.93%
	More than 20001	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. Confirmatory factor analysis (CFA) was developed to determine the influence of variables on the adoption of AVs. The data needed to be evaluated the reliability and validity before performing CFA. Table 4 provides details of the reliability and convergent validity of constructs. The standardized factor loadings of 12 observed variables ranged from 0.851 to 0.961, exceeding the standard of 0.5 [67]. All Cronbach's alpha values of 4 latent variables were above the acceptable level of 0.70[68]. The minimum composite reliability (CR) value was 0.921, and all values were higher than the minimum threshold of 0.7 [69]. The average variance extracted (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 shows the results of the discriminant validity test. 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			

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 29 August 2023 doi:10.20944/preprints202308.1939.v1

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 value 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 ($\chi^2/_{df}$), 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).

$\chi^2/_{df}$=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 strength 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 BIC and CAIC were proposed to penalize the number of classes. Table 6 summarizes these measures concerning the models with classes between one to six. 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 perform better than the no 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	10011.2	10011.2	10055.3	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							

The selected 4-segment model has a rho-bar squared 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. Segment

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 29 August 2023 doi:10.20944/preprints202308.1939.v1

4 only accounts for 7.3% of the sample, with the coefficient of walking and waiting time positively significant while the coefficient of in-vehicle time and trip cost statistically insignificant. The results mean that the respondents of this segment failed to understand the choice task fully.

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	-.856**	0.423	-1.421***	0.435	-0.635	0.430	0	
Associate degree	-0.072	0.448	0.796*	0.427	-0.572	0.491	0	
Bachelor degree	.830***	0.318	1.152***	0.325	.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 5000	0.201	0.382	0.687*	0.384	0.148	0.385	0	
10001-20000	1.068*	0.549	1.279**	0.551	1.450***	0.550	0	

Segment 1 comprises 28.7% of the sample. The parameter estimates and corresponding z-values in segment 1 indicate that 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. Most respondents favored walk (93.9%), while a smaller preferred shared bikes (4.8%). The results indicate that class 1 is interested in walking. According to the class member model, respondents who belonged to class 1 are more likely to possess bachelor's degrees and upper middle income (10001-20000 CNY monthly) and are less likely to own 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 regarding AV BIU contributes positively to the total utility, indicating that a higher AV BIU decreases the disutility for AVs for the last mile trip.

Segment 2 consists of 37.8% of the respondents. Travelers, who opt for walk, shared bikes, shared AVs, and buses, accounted for 21.8%, 33.5%, 16.2%, and 28.4%. They are more likely to have a bachelor's degree, work in public servants/public institutions and Enterprise employees, and have middle income compared with other classes. 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. The results may indicate that respondents in segment 2 are not familiar with AVs.

Segment 3 includes 26.2% of the sample. With 91.3% choosing shared bikes, it is dominated by those who are more likely to take a bike for the last mile. In terms of socio-characteristics, individuals in this class 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 provides the direct and cross elasticities of the travel cost for all travel modes to study the preference difference among the three LCs, except the residual class 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 AV leads to a 0.649% decrease in the choice probability of shared AV (i.e., direct elasticity), while it causes a 0.105% increase in the probability of choosing walk, shared bike, and bus (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

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 29 August 2023 doi:10.20944/preprints202308.1939.v1

of class1 are smaller than negative1 and them in 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 AV leads to a 7.598% decrease in the choice probability of shared AV.

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

Table 10 shows travelers' willingness to pay for each of the segments. Individuals from segment 1 who are sensitive to travel costs were willing to pay 14.5 CNY to reduce 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 for as much as 441.3 CNY and 63.0 CNY to decrease one-hour walking and waiting time and in-vehicle time. The results are consistent with previous research. Seelhorst and Liu (2015) found 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 multimodal train 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 train 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 enterprise employees with a middle income.

The impact of latent psychological variables on different groups is significantly different. The latent psychological variables of AVs have no significant impact on the trips of travelers from

 doi:10.20944/preprints202308.1939.v1

segment 2, indicating that travelers lack sufficient knowledge of 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 AV leads to a 7.598% decrease in the choice probability of shared AV. 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 AV.

Travelers from different segments have different willingness to pay for walking and waiting time and in-vehicle time. In-vehicle time has an insignificant effect on travelers from segment 1. Unlike travelers from segment 1, travelers from segment 2 are willing to pay 20.4 CNY to reduce one-hour In-vehicle time, while travelers from segment 3 are willing to pay 60.3 CNY to reduce one-hour in-vehicle time. Walking and waiting time significantly impact travelers from all segments, but the magnitude of the impact varies greatly. Travelers from segment 2 are willing to pay 11.0 CNY to reduce one-hour walking and waiting time, while travelers from segment 3 are willing to pay up to 441.3 CNY to reduce one-hour walking and waiting time. The results show that the value of travel time for high-income groups is relatively higher.

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 train trips. Although the Avs have been studied in the Netherlands, Atlanta area, Ann Arbor-Detroit Area, and other areas [3,4,75], the results of these areas are not applicable to other areas.

From the perspective of research methods, this paper is different from the existing research, which uses cluster analysis to identify user groups [76]. This paper is the first time that used the LC logit model to study travelers' preferences to choose shared AVs to solve the last mile problem of train 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]. 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 paper still needs to be further studied. Firstly, the results of this paper are mainly for the research area. Research results in different countries and regions will also vary. Secondly, the COVID-19 has an important impact on the travel behavior of travelers. Future research can consider the impact of COVID-19 on travelers' preference for shared AVs. Finally, this paper mainly studies the option of train and transfer while ignoring the option of private AVs throughout the journey. More options for travel indicate more complex the system and greater uncertainty. Studying more modes of travel helps to understand this uncertainty.

Author Contributions: Conceptualization, Zhiwei Liu and Jianrong Liu; Data curation, Zhiwei Liu; Formal analysis, Zhiwei Liu and Jianrong Liu; Funding acquisition, Zhiwei Liu; Investigation, Zhiwei Liu and Jianrong Liu; Methodology, Zhiwei Liu and Jianrong Liu; Software, Zhiwei Liu and Jianrong Liu; Validation, Zhiwei Liu and Jianrong Liu. All authors have read and agreed to the published version of the manuscript.

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The data presented in this study are available on request from the corresponding author. The data are not publicly available due to privacy.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Zhao, R., et al., Last-mile travel mode choice: Data-mining hybrid with multiple attribute decision making. 2019. 11(23): p. 6733.
2. Zhou, J., et al., The implications of high-speed rail for Chinese cities: Connectivity and accessibility. 2018. 116: p. 308-326.
3. Yap, M.D., G. Correia, and B. Van Arem, Preferences of travellers for using automated vehicles as last mile public transport of multimodal train trips. Transportation research part a: policy and practice, 2016. 94: p. 1-16.
4. Moorthy, A., et al., Shared autonomous vehicles as a sustainable solution to the last mile problem: A case study of Ann Arbor-Detroit area. 2017. 10(2017-01-1276): p. 328-336.
5. Bauman, A.E., et al., Correlates of physical activity: why are some people physically active and others not? 2012. 380(9838): p. 258-271.
6. Buehler, R., et al., Physical activity from walking and cycling for daily travel in the United States, 2001?©2017: Demographic, socioeconomic, and geographic variation. 2020. 16: p. 100811.
7. Munoz-Raskin, R., Walking accessibility to bus rapid transit: Does it affect property values?The case of Bogotá, Colombia. Transport policy, 2010. 17(2): p. 72-84.
8. Taeihagh, A. and H.S.M.J.T.r. Lim, Governing autonomous vehicles: emerging responses for safety, liability, privacy, cybersecurity, and industry risks. 2019. 39(1): p. 103-128.
9. Kyriakidis, M., et al., Public opinion on automated driving: Results of an international questionnaire among 5000 respondents. 2015. 32: p. 127-140.
10. Milakis, D., M. Kroesen, and B.J.J.o.T.G. van Wee, Implications of automated vehicles for accessibility and location choices: Evidence from an expert-based experiment. 2018. 68: p. 142-148.
11. Alazzawi, S., et al., Simulating the impact of shared, autonomous vehicles on urban mobility-a case study of Milan. 2018. 2: p. 94-110.
12. Martinez, L.M., J.M.J.I.J.o.T.S. Viegas, and Technology, Assessing the impacts of deploying a shared self-driving urban mobility system: An agent-based model applied to the city of Lisbon, Portugal. 2017. 6(1): p. 13-27.
13. Jones, E.C., B.D.J.T.R.P.D.T. Leibowicz, and Environment, Contributions of shared autonomous vehicles to climate change mitigation. 2019. 72: p. 279-298.
14. Schoettle, B. and M. Sivak, A survey of public opinion about autonomous and self-driving vehicles in the US, the UK, and Australia. 2014, University of Michigan, Ann Arbor, Transportation Research Institute.
15. Shabanpour, R., et al. Consumer preferences of electric and automated vehicles. in 2017 5th IEEE International Conference on Models and Technologies for Intelligent Transportation Systems (MT-ITS). 2017. IEEE.
16. Bauer, G.S., et al., Cost, energy, and environmental impact of automated electric taxi fleets in Manhattan. 2018. 52(8): p. 4920-4928.
17. Fagnant, D.J. and K.M.J.T. Kockelman, Dynamic ride-sharing and fleet sizing for a system of shared autonomous vehicles in Austin, Texas. 2018. 45(1): p. 143-158.
18. König, M., L.J.T.r.p.F.t.p. Neumayr, and behaviour, Users' resistance towards radical innovations: The case of the self-driving car. 2017. 44: p. 42-52.
19. Shabanpour, R., et al., Eliciting preferences for adoption of fully automated vehicles using best-worst analysis. 2018. 93: p. 463-478.
20. Bansal, P., K.M.J.T.R.P.A.P. Kockelman, and Practice, Forecasting Americans' long-term adoption of connected and autonomous vehicle technologies. 2017. 95: p. 49-63.
21. Liu, J., et al., Tracking a system of shared autonomous vehicles across the Austin, Texas network using agent-based simulation. 2017. 44(6): p. 1261-1278.
22. Soteropoulos, A., M. Berger, and F.J.T.r. Ciari, Impacts of automated vehicles on travel behaviour and land use: an international review of modelling studies. 2019. 39(1): p. 29-49.
23. Lokhandwala, M. and H.J.T.R.P.C.E.T. Cai, Dynamic ride sharing using traditional taxis and shared autonomous taxis: A case study of NYC. 2018. 97: p. 45-60.
24. Moreno, A.T., et al., Shared autonomous vehicles effect on vehicle-km traveled and average trip duration. 2018. 2018.
25. Webb, J., et al., Will people accept shared autonomous electric vehicles? A survey before and after receipt of the costs and benefits. 2019. 61: p. 118-135.
26. Stoiber, T., et al., Will consumers prefer shared and pooled-use autonomous vehicles? A stated choice experiment with Swiss households. 2019. 71: p. 265-282.
27. Bösch, P.M., F. Ciari, and K.W.J.T.R.R. Axhausen, Transport policy optimization with autonomous vehicles. 2018. 2672(8): p. 698-707.
28. Chen, T.D. and K.M.J.T.R.R. Kockelman, Management of a shared autonomous electric vehicle fleet: Implications of pricing schemes. 2016. 2572(1): p. 37-46.

29. Childress, S., et al., Using an activity-based model to explore the potential impacts of automated vehicles. 2015. 2493(1): p. 99-106.
30. Kim, K., et al. The travel impact of autonomous vehicles in metro Atlanta through activity-based modeling. in The 15th TRB National Transportation Planning Applications Conference. 2015.
31. Gkartzonikas, C. and K. Gkritza, What have we learned? A review of stated preference and choice studies on autonomous vehicles. Transportation Research Part C: Emerging Technologies, 2019. 98: p. 323-337.
32. de Dios Ortuzar, J., Nested logit models for mixed-mode travel in urban corridors. Transportation Research Part A: General, 1983. 17(4): p. 283-299.
33. Stern, S.P., A disaggregate discrete choice model of transportation demand by elderly and disabled people in rural Virginia. Transportation research part a: policy and practice, 1993. 27(4): p. 315-327.
34. Ewing, R., W. Schroeer, and W.J.T.r.r. Greene, School location and student travel analysis of factors affecting mode choice. 2004. 1895(1): p. 55-63.
35. Frank, L., et al., Urban form, travel time, and cost relationships with tour complexity and mode choice. Transportation Research Part A: General, 2008. 35(1): p. 37-54.
36. Wang, Q., et al., Urban travel mode split optimization based on travel costs. 2014. 138: p. 706-714.
37. Schwanen, T., M. Dijst, and F.M.J.T.v.e.e.s.g. Dieleman, Leisure trips of senior citizens: determinants of modal choice. 2001. 92(3): p. 347-360.
38. Zhang, M.J.J.o.t.A.p.a., The role of land use in travel mode choice: Evidence from Boston and Hong Kong. Journal of the American planning association, 2004. 70(3): p. 344-360.
39. Verplanken, B., et al., Context change and travel mode choice: Combining the habit discontinuity and self-activation hypotheses. 2008. 28(2): p. 121-127.
40. Tilahun, N., et al., Transit use and the work commute: Analyzing the role of last mile issues. 2016. 54: p. 359-368.
41. Paulssen, M., et al., Values, attitudes and travel behavior: a hierarchical latent variable mixed logit model of travel mode choice. Transportation, 2014. 41(4): p. 873-888.
42. Hagman, O., Mobilizing meanings of mobility: car users' constructions of the goods and bads of car use. Transportation research part D: Transport environment, 2003. 8(1): p. 1-9.
43. Sanbonmatsu, D.M., et al., Cognitive underpinnings of beliefs and confidence in beliefs about fully automated vehicles. Transportation research part F: traffic psychology and behaviour, 2018. 55: p. 114-122.
44. Panagiotopoulos, I. and G. Dimitrakopoulos, An empirical investigation on consumers' intentions towards autonomous driving. Transportation research part C: emerging technologies, 2018. 95: p. 773-784.
45. Choi, J.K. and Y.G. Ji, Investigating the importance of trust on adopting an autonomous vehicle. International Journal of Human-Computer Interaction, 2015. 31(10): p. 692-702.
46. Kaur, K. and G. Rampersad, Trust in driverless cars: Investigating key factors influencing the adoption of driverless cars. Journal of Engineering Technology Management, 2018. 48: p. 87-96.
47. Haboucha, C.J., R. Ishaq, and Y. Shiftan, User preferences regarding autonomous vehicles. Transportation Research Part C: Emerging Technologies, 2017. 78: p. 37-49.
48. Lavieri, P.S. and C.R. Bhat, Modeling individuals' willingness to share trips with strangers in an autonomous vehicle future. Transportation research part A: policy practice, 2019. 124: p. 242-261.
49. Ye, F. and D. Lord, Comparing three commonly used crash severity models on sample size requirements: Multinomial logit, ordered probit and mixed logit models. Analytic methods in accident research, 2014. 1: p. 72-85.
50. Chipman, J.S., The foundations of utility. Econometrica: Journal of the Econometric Society, 1960: p. 193-224.
51. Luce, R.D., Individual choice behavior: A theoretical analysis. 2012: Courier Corporation.
52. Hensher, D.A., HEV choice models as a search engine for the specification of nested logit tree structures. Marketing Letters, 1999. 10(4): p. 333-343.
53. McFadden, D. and K. Train, Mixed MNL models for discrete response. Journal of applied Econometrics, 2000. 15(5): p. 447-470.
54. Revelt, D. and K. Train, Mixed logit with repeated choices: Households' choices of appliance efficiency level. Review of economics statistics, 1998. 80(4): p. 647-657.
55. Lee, B.J., et al. Analysis of mode choice behaviours based on latent class models. in 10th International Conference on Travel Behaviour Research, Lucerne. 2003.
56. Greene, W.H. and D.A. Hensher, A latent class model for discrete choice analysis: contrasts with mixed logit. Transportation Research Part B: Methodological, 2003. 37(8): p. 681-698.
57. Massiani, J., R. Danielis, and E. Marcucci, THE HETEROGENEITY IN SHIPPER'S VALUE OF TIME, RESULTS FROM AN SP EXPERIMENT USING MIXED LOGIT AND LATENT CLASS. Pomorstvo/Journal of Maritime Studies, 2007. 21(2).
58. Greene, W.H. and D.A. Hensher, Revealing additional dimensions of preference heterogeneity in a latent class mixed multinomial logit model. Applied Economics, 2013. 45(14): p. 1897-1902.

doi:10.20944/preprints202308.1939.v1

59. Ajzen, I., The theory of planned behavior. Organizational behavior human decision processes, 1991. 50(2): p. 179-211.
60. Jing, P., et al., Exploring the factors affecting mode choice Intention of autonomous vehicle based on an extended theory of planned behavior—A case study in China. Sustainability, 2019. 11(4): p. 1155.
61. Donald, I.J., S.R. Cooper, and S.M. Conchie, An extended theory of planned behaviour model of the psychological factors affecting commuters' transport mode use. Journal of environmental psychology, 2014. 40: p. 39-48.
62. Lanzini, P. and S.A. Khan, Shedding light on the psychological and behavioral determinants of travel mode choice: A meta-analysis. Transportation research part F: traffic psychology behaviour, 2017. 48: p. 13-27.
63. Liu, P., R. Yang, and Z. Xu, Public acceptance of fully automated driving: Effects of social trust and risk/benefit perceptions. Risk Analysis, 2019. 39(2): p. 326-341.
64. Biernacki, C. and G. Govaert, Choosing models in model-based clustering and discriminant analysis. Journal of Statistical Computation and Simulation, 1999. 64(1): p. 49-71.
65. Anderson, D., K. Burnham, and G. White, Comparison of Akaike information criterion and consistent Akaike information criterion for model selection and statistical inference from capture-recapture studies. Journal of Applied Statistics, 1998. 25(2): p. 263-282.
66. JMP, A.B.U.o.S. and M. Proust, Design of experiments guide. 2010, Cary, NC: SAS Institute Inc.
67. Tracey, M., M.A. Vonderembse, and J.-S. Lim, Manufacturing technology and strategy formulation: keys to enhancing competitiveness and improving performance. Journal of operations management, 1999. 17(4): p. 411-428.
68. Kline, R.B., Principles and practice of structural equation modeling. Guilford Press. 2005, New York. 59.
69. Fornell, C. and D.F. Larcker, Evaluating structural equation models with unobservable variables and measurement error. Journal of marketing research, 1981. 18(1): p. 39-50.
70. Wang, J. and X. Wang, Structural equation modeling: Applications using Mplus. 2019: John Wiley & Sons.
71. Marsh, H.W., J.R. Balla, and K.-T. Hau, An evaluation of incremental fit indices: A clarification of mathematical and empirical properties. Advanced structural equation modeling: Issues, 1996: p. 315-353.
72. Taasoobshirazi, G. and S. Wang, The performance of the SRMR, RMSEA, CFI, and TLI: An examination of sample size, path size, and degrees of freedom. Journal of Applied Quantitative Methods, 2016. 11(3): p. 31-39.
73. Seelhorst, M. and Y. Liu, Latent air travel preferences: Understanding the role of frequent flyer programs on itinerary choice. Transportation Research Part A: Policy and Practice, 2015. 80: p. 49-61.
74. Wen, C.-H. and S.-C. Lai, Latent class models of international air carrier choice. Transportation Research Part E: Logistics and Transportation Review, 2010. 46(2): p. 211-221.
75. Walls, D.B., Assessing the potential of autonomous transit shuttles as a first-and-last mile public transportation solution. 2018, Georgia Institute of Technology.
76. Alonso-González, M.J., et al., Drivers and barriers in adopting Mobility as a Service (MaaS)–A latent class cluster analysis of attitudes. Transportation Research Part A: Policy and Practice, 2020. 132: p. 378-401.