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Modelling Passengers' Travel Behaviour for Shared Autonomous Vehicle and Bus Considering Heterogeneity

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ABSTRACT

The popularisation of autonomous vehicles will give rise to a new business model called shared autonomous vehicle (SAV). SAVs may attract a large number of passengers and lead to a decline in the share of buses, which can be interpreted by exploring passengers' travel behaviour when confronting the SAV and bus modes. Thus, this paper addresses the SAV and bus passengers' travel behaviour, aiming to examine the factors influencing travel behaviour and revealing the characteristics of SAV passengers. We classified passengers using latent class cluster analysis and modelled passengers' travel behaviour based on confirmatory factor analysis and mixed logit model. The findings indicate a variation in travel preferences among different classes of travellers. Short-distance travellers pay less attention to travel time. Non-short-distance PT travellers are most likely to be affected by service attributes (waiting time, travel time and travel costs). Non-short-distance private car travellers are more likely to become early SAV adopters. Passengers travelling for short distances may be more likely to choose SAV, which reveals the potential of SAVs to become a first and last mile connection for public transport. Passengers lack trust in SAVs, which will affect their promotion.

KEYWORDS

shared autonomous vehicle; bus; travel behaviour; heterogeneity; mixed logit model

1. INTRODUCTION

Concurrent with the recent rapid technological evolution, autonomous vehicles (AV) are undergoing pilot testing in diverse regions across the globe [1]. AV technologies are anticipated to bring about a significant transformation in the transportation industry [2]. Some studies have shown that with the commercialisation of AVs, human-driven cars will gradually be replaced by AVs [3,4], which will result in the share of cars declining and inversely the share of AVs increasing [5]. Given the exorbitant cost associated with privately owned autonomous vehicles (PAV) and the growing prevalence of mobility-as-a-service (MaaS), it is anticipated that a majority of people will not opt to purchase PAV, instead choosing to use shared autonomous vehicle (SAV) services [6]. SAV combines AV with traditional car sharing and taxi services, also known as autonomous taxis, which can offer on-demand mobility services [7]. Via an app, a passenger initiates travel requests, and an SAV transfers the passenger from the departure location to the designated destination. Thus, in the era of autonomous driving, the motorised transportation modes on the ground in urban areas primarily encompass SAV and bus. These two modes collaboratively engage in the provision of transportation services for travellers.

The fares associated with utilising SAVs are expected to be low due to the absence of driver labour costs. The cost of SAVs is comparable to that of public transportation [8]. SAVs can provide a more convenient service than bus because they eliminate the process of walking to a stop and waiting there, instead offering door-to-door passenger transportation. Therefore, SAVs may have the potential to attract a large number of travellers, leading to a decline in the share of bus and posing a threat to this mode, which may exacerbate urban traffic in the AV era. This can be answered by exploring passengers' travel behaviour when confronting SAV and bus choices. This study investigates passengers' travel behaviour for SAV and bus considering an existing heterogeneity among passengers. We first segmented passengers into different classes and then modelled passenger travel behaviour for each class considering service attributes, socioeconomics, historical travel behaviour and attitudes. The primary objectives are to uncover the factors influencing passengers' mode choice and identify travel behaviour in different classes of passengers when they confront the modes of SAV and bus.

The organisation of this paper is as follows: Section 2 introduces a literature review. Section 3 details the survey methodology and data collection process. In Section 4, we present methods for modelling passenger travel behaviour for SAV and bus considering heterogeneity. The results of the model are displayed in Section 5, followed by the discussion and conclusions in Section 6.

2. LITERATURE REVIEW

The issue of travel behaviour for SAV as a new mode has attracted great interest in recent years. Early research on preferences for SAV focused on service attributes (e.g. travel time, wait time, travel cost) and socioeconomic attributes. Krueger et al. [7] conducted an online survey on 435 respondents from major metropolitan areas in Australia to examine their preference for SAV. Utilising a mixed logit model for data analysis, the findings revealed that waiting time, travel time and travel cost are important determinants of SAV use. Furthermore, SAV adoption varies among different groups, with younger individuals and those using multiple modes of transportation being more inclined to use SAV. Haboucha et al. [9] conducted an intention survey among 721 respondents in Israel and North America to study SAV acceptance, and the collected data was analysed using a logit model. They discovered that early autonomous driving adopters might be younger individuals, students, those with higher education and people who spend considerable time in vehicles. Additionally, approximately a quarter of respondents indicated they would not utilise an SAV, even if it were free of charge.

In addition to service attributes and socioeconomic attributes, researchers have found that passenger attitudes also play an important role in SAV preference, and they added the influence of attitudes to SAV preferences in the model. Nazari et al. [6] used a multivariate ordered probit model to analyse the stated preference data gathered in the Puget Sound regional travel survey. The results found that young men using private cars, living in multi-person households and single-function communities were interested in private AVs. Concerns about safety present obstacles to the public embracement of SAVs, even as enthusiasm for them is bolstered by a commitment to sustainable travel behaviours and an understanding of on-demand mobility solutions. An internet-based survey was conducted by Bansal et al. [10] with a sample of 347 Austin residents to gain insights into their attitudes toward SAVs. The data indicates that individuals with elevated income levels, a tech-savvy disposition, urban dwellers and those with a history of experiencing more traffic incidents are more inclined and willing to invest in SAV adoption. Maeng and Cho [11] surveyed 1000 respondents aged from 20 to 69 in South Korea and estimated their preference and willingness to pay for an SAV service using a mixed multiple discrete-continuous extreme value (MDCEV) model. The findings indicate that as autonomous driving technology advances, there is a growing inclination among individuals to embrace SAV services.

Passengers' travel mode preferences are heterogeneous. The method of passenger segmenting is often used to address heterogeneity among passengers. Rahimi et al. [12] studied the adoption and willingness to pay (WTP) for SAV using latent class cluster analysis to divide respondents from the state of Florida into three different user categories. The results showed that the attitudes and WTP for each category were different among the three categories. Etzioni et al. [13] divided Israeli passengers into two latent categories and found the two categories of passengers had different preferences.

In summary, passengers' travel behaviour after the introduction of SAV was well investigated. However, there is a gap in research in terms of passengers' travel behaviour when confronting the SAV and bus modes.

Passengers' travel behaviour with SAVs for passengers from regions like North America, Australia, Korea and Israel has been investigated. However, there is a lack of studies paying attention to Chinese SAV preferences. China's population accounts for approximately 18% of the global population, and China will be one of the key SAV markets. Hence, this study explores Chinese travel behaviour for SAV and bus.

3. DATA COLLECTION

This section describes questionnaire design and data collection. In light of the unavailability of SAV on the market at present, we opted for a stated preference survey. Respondents' preferences for SAV and bus were studied by examining their SAV and bus choice behaviour in a hypothetical situation. Additionally, we have incorporated an attitude survey into the questionnaire to examine respondents' attitudes toward SAV.

3.1 Survey and sample

An online survey was developed, consisting of four parts. Socioeconomic indicators, including attributes like age, gender and educational background, were captured in the first segment. The next segment inquired about historical travel behaviour, including travel mode, time, cost and travel distance. The third part contains the stated preference (SP) surveys. The last part measures the respondents' attitudes toward SAV.

At the beginning of the questionnaire, SAVs were briefly introduced to the respondents, reading as follows: "Shared autonomous vehicles integrate traditional taxi services with autonomous driving. They can provide cheap, convenient and comfortable on-demand travel services. The passenger makes an appointment with the operator through a mobile app, and a shared autonomous vehicle will pick up the passenger at the reserved location and send it to the destination. The passenger does not need to stop after arriving at their destination, and the shared autonomous vehicle leaves and continues to pick up the next passenger."

The questionnaire was entrusted to Wenjuanxing (a professional survey research firm) to collect the data for this survey, which was completed in January 2022. The survey locations selected for this study were Beijing and Shanghai. These two cities serve as international hubs for exchange and technological innovation. Currently, there are pilot projects related to autonomous driving in Beijing and Shanghai. They are the most promising regions in China to take the lead in SAV deployment and have broad application markets. A total of 704 questionnaires were collected in this survey. We identified the questionnaires that took less than 3 minutes to answer or those containing multiple consecutive questions answered with the same option as invalid. After filtering out the invalid questionnaires, we amassed a total of 627 valid samples, with a corresponding validity percentage of 89.06%.

3.2 Design of stated preference survey

In *Table 1*, we present a detailed summary of service attributes utilised in our SP experiments, accompanied by their associated attribute levels. The attribute level of each attribute is designed based on a travel distance of 10 km (the average commuting distance in Beijing and Shanghai is 10 km). This study employed an orthogonal design methodology, resulting in the acquisition of a total of 18 survey scenarios. Respondents chose either SAV or bus for travel in each SP experiment. Respondents based their choice on wait times, travel times and travel costs for each mode of travel. To reduce the respondents' impatience and enhance the precision of the findings, each respondent was randomly selected to answer 5 out of 18 SP experiments. This meant that 5*627=3135 choices were obtained. *Figure 1* shows an example of an SP experiment.

Table 1 – Service attributes and attribute levels used in the SP experiment

Mode	Service attributes	Attribute levels	Mode	Service attributes	Attribute levels
SAV	Waiting time	2 min, 5 min, 8 min	bus	Waiting time	10 min, 15 min, 20 min
	Travel time	15 min, 20 min, 25 min		Travel time	35 min, 40 min, 45 min
	Travel cost	10 yuan, 15 yuan, 20 yuan		Travel cost	2 yuan, 3 yuan, 4 yuan

Assuming the distance to your place of work (school) is **10 kilometers**. There are two available travel modes to choose from: **SAV and bus**. The choice of travel modes is not influenced by temperature or weather. When the waiting time, travel time, and travel cost are shown in the table below, which mode would you choose?

	Waiting time	Travel time	Travel cost
SAV	5 min	20 min	10 yuan
bus	15 min	41 in	4 yuan

☐ Alternative 1: SAV

☐ Alternative 2: bus

Figure 1 – An example of an SP experiment

3.3 Design of attitudes

Passengers' selection of behaviours can be profoundly influenced by their attitudes. In this research, passengers' attitudes toward SAV were reflected through psychological latent variables. Considering that SAV is an emerging technology, the selection of psychological latent variables in this study refers to the technology acceptance model (TAM) [14], which has been applied to evaluate technology acceptance in a variety of fields. Considering the TAM and combined with previous research [9, 10, 15–18], we selected five latent variables to reflect passengers' attitudes toward SAV: Perceived Risk (PR), Perceived Usefulness (PU), Perceived Ease of Use (PEU), Perceived Trust (PT) and Willingness to Use (WU). *Table 2* contains the manifest indicators, items and sources corresponding to each latent variable. A five-point Likert-type scale, ranging from "strongly disagree (=1)" to "strongly agree (=5)", was utilised to evaluate all manifest indicators.

Table 2 – Manifest indicators, items and sources of latent variables

Latent variables	**Manifest indicators**	**Items**	**Sources**
Perceived Risk (PR)	I'm concerned about a device or system failure in an SAV.	PR1	[10,18]
	I'm concerned that the computer systems of SAV have been hacked.	PR2	
	I'm worried about privacy leaks after using SAV.	PR3	
Perceived Usefulness (PU)	When I use an SAV, I will have more time to do other things in SAV (e.g. reading, working, resting, playing etc.).	PU1	[16,18]
	SAV could reduce my travel time.	PU2	
	SAV can improve my travel safety.	PU3	
Perceived Ease of Use (PEU)	I think it's easier to use an SAV than a manual car.	PEU1	[10,18]
	I can easily grasp the SAV booking process.	PEU2	
	I have no psychological burden to use an SAV.	PEU3	
Perceived Trust (PT)	By booking an SAV, I ensure my family is transported.	PT1	[9,15,18]
	In the future of travel, I support autonomous driving instead of human driving.	PT2	
	I think riding a shared autonomous vehicle is enjoyable and fun.	PT3	
Willingness to Use (WU)	In the future, I will use SAV.	WU1	[15,17]
	When SAV are on the market and I need to travel by car, I will give priority to using SAV.	WU2	
	I would recommend SAV to friends and family.	WU3	

4. DATA COLLECTION

We classified passengers using latent class cluster analysis and modelled passengers' travel behaviour based on confirmatory factor analysis and mixed logit model. In addition, we also estimated the marginal effects of service attributes.

4.1 Latent class cluster analysis

Latent class cluster analysis (LCCA) is a method of clustering based on probabilistic models, which does not rely on the distance between elements to categorise them into groups [19]. It is presumptive that an unobserved or latent categorical variable divides all data into exclusive latent classes. It is used to divide the entire dataset into several clusters that maximise the heterogeneity between these clusters. The literature shows that LCCA outperforms K-means in terms of model performance [20].

Suppose a dataset is divided into C classes. Let each passenger i in the sample contain M indicator variables. Each indicator variable can take values from a set of R_m possible outcomes. Let γ_c denote the probability that a passenger falls into class c(c=1,2,...,C). ρ denotes the probability that passenger i has the property of all M features conditioned on latent class membership. Y_{imr}=1 if the m-th categorical variable of passenger i is the r-th result, otherwise Y_{imr}=C. Therefore, $\rho_{mcr}^{Y_{mcr}}$ represents the probability that the m-th variable of passenger i produces the r-th result in the c class. Then the probability of a given passenger can be given by:

$$P(Y_i|\rho,\gamma)=\sum_{c=1}^{C}\gamma_c\prod_{m=1}^{M}\prod_{r=1}^{R_m}\rho_{mcr}^{Y_{imr}} \tag{1}$$

4.2 Mixed logit model

The mixed logit model (random parameters logit model) is a discrete choice model based on utility maximisation theory. Passengers will choose j when the utility U_j of the j-th option is higher than the others. In the present research, the mixed logit model is employed to examine the travel behaviour of passengers regarding SAV and bus. We constructed a mixed logit model framework consisting of four components. Passengers face a choice among J travel modes. For a passenger n under latent class c*,* the utility of choosing travel mode j is represented as:

$$U_{nj}=\beta_x^{'}x_{nj}+\beta_s^{'}s_{nj}+\beta_h^{'}h_{nj}+\beta_a^{'}a_{nj}+\varepsilon_{nj} \tag{2}$$

where x_{nj}, s_{nj}, h_{nj}, a_{nj} represent the vectors of independent variables, which are the service attributes vector, socioeconomic variables vector, socioeconomic variables vector and attitudes vector. β_x', β_s', β_h', β_a', are the vectors of unknown parameters that are to be estimated. ε_{nj} is the error term that is an independent and identically distributed extreme value.

$\beta_x'x_{nj}$ is the part of the service attributes in the utility function U_{nj}, which is the core of the model. x_{nj} is the corresponding service attributes vector in the SP experiment, which consists of waiting time, travel time and travel cost. β_x' is the vector of unknown parameters to be estimated, corresponding to service attributes.

$\beta_x's_{nj}$ represents socioeconomic variables in *Equation 2*. s_{nj} represents the vector of socioeconomic variables. β_s' is the vector of unknown parameters to be estimated within the socioeconomic variables.

$\beta_x'h_n$ is similar, h_{nj} represents a vector of historical travel behaviours, and β_h' is the vector of unknown parameters to be estimated within the historical travel behaviours.

Passengers' attitudes will play a significant role in SAV adoption. Incorporating public attitude surveys into the model can be a more realistic representation of choice behaviour, giving the model better explanatory power. In this study, we incorporated the latent variable score into the model. Before predicting latent variable scores, a confirmatory factor analysis is required.

Confirmatory factor analysis (CFA) is used to examine how well the manifest indicators represent latent variables. It is a multivariate statistical method used to examine the psychometric properties of scales. Utilising CFA, this research examines if the association between a latent variable and its manifest indicators aligns with the designed theoretical relationship. Their relationship is expressed by the following formula:

$$Y=\Lambda\eta+\delta \tag{3}$$

where Y, η and δ are manifest indicators, latent variables and measurement errors, respectively, and Λ is a factor fit matrix.

CFA is performed on samples from each latent class separately to examine the extent to which the manifest indicators represent the latent variables. If the CFA results show good reliability and validity, then the corresponding latent variable scores can be predicted based on the manifest indicators.

$\beta_a'a_{nj}$ means passengers' attitudes toward SAV in *Equation 2*. a_{nj} is the vector of latent variable scores, using latent variable scores to indicate passenger attitudes to SAV. β_a' is the vector of unknown parameters to be estimated.

Based on the content of the four parts $\beta_x' x_{nj}$, $\beta_s' s_{nj}$, $\beta_s' h_{nj}$ and $\beta_a' a_{nj}$, the logit probability of passenger n choosing travel modes j can be obtained (conditional on β) as:

$$P_{nj}(\beta) = \frac{exp(\beta_x' x_{nj} + \beta_s' s_{nj} + \beta_h' h_{nj} + \beta_a' a_{nj})}{\sum_{j=1}^{J} exp(\beta_x' x_{nj} + \beta_s' s_{nj} + \beta_h' h_{nj} + \beta_a' a_{nj})} \tag{4}$$

The unconditional choice probability is the expected value of the logit probability over all the possible values of β, that is, integrated over these values, weighted by the density of β. The unconditional probability that passenger n chooses travel modes j can be expressed as:

$$P_{nj}(\beta) = \int \left(\frac{exp(\beta_x' x_{nj} + \beta_s' s_{nj} + \beta_h' h_{nj} + \beta_a' a_{nj})}{\sum_{j=1}^{J} exp(\beta_x' x_{nj} + \beta_s' s_{nj} + \beta_h' h_{nj} + \beta_a' a_{nj})} \right) f(\beta | \theta) d\beta \tag{5}$$

Equation 5 is the mixed logit probability, the model of this form is called the mixed logit [21, 22].

4.3 Marginal effects

In this study, marginal effects are used to analyse the change in the probability of passengers choosing travel mode j caused by a one-unit increase in the service attribute value. Marginal effects are calculated as follows:

$$E(x_{jk}) = \frac{\partial P_j}{\partial x_{jk}} \tag{6}$$

Where $E(x_{jk})$ is the marginal effects value of the probability of choosing travel mode j to service attribute k, P_j is the probability that the passenger chooses travel mode j, x_{jk} is the value of service attribute k of travel mode j.

5. RESULTS

The outcomes stemming from the model's estimation are clarified in this section. Firstly, samples are partitioned into three unique classes using LCCA. Secondly, we illustrate the CFA results for each class and predict the scores of latent variables. In the third part, we analyse the model estimations results of passengers' travel behaviour for SAV and bus. The final section showcases the marginal effects of service attributes.

5.1 Passenger classification results

To capture passenger heterogeneity we use historical travel behaviour and occupation as indicator variables. Mplus version 8.3 is used to perform latent class clustering analysis on samples. We estimate models from two to seven classes. *Figure 2* shows the fit statistics for two to seven class models. In this study, AIC, BIC, aBIC and entropy are selected to choose an appropriate number of latent classes. The first three metrics are commonly used to check model fitness, and the last one can show the accuracy of the classification.

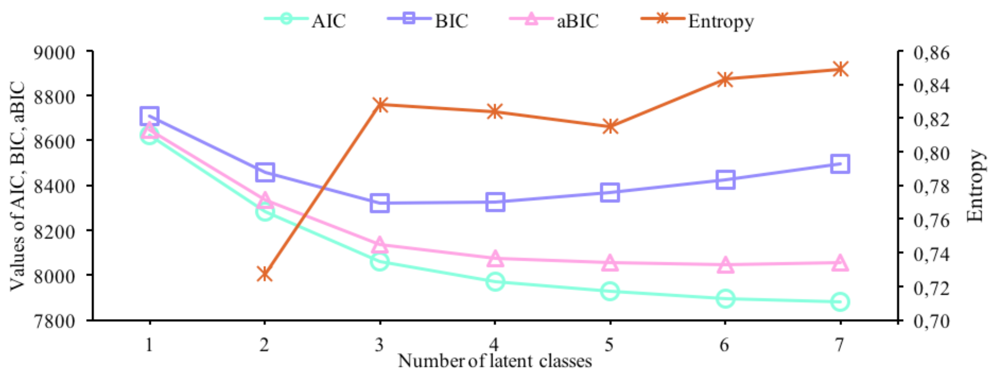

Figure 2 – AIC, BIC, aBIC, and entropy values for different latent classes

As can be seen in *Figure 2*, AIC and aBIC decrease as the number of clusters increases, and BIC is minimum when the number of latent classes is three. The percentage decrease in AIC and aBIC drops to less than

1% from three latent classes onwards. This means that three latent classes can separate the data satisfactorily. Meanwhile, the value of entropy is 0.828>0.8 when dividing the samples into three latent classes, indicating that the classification accuracy is more than 90% [23]. When the sample is divided into three latent classes, the p-values for both LMR and BLRT are below 0.05. When the sample is divided into four latent classes, the value of LMR is 0.056 greater than 0.05. Consequently, partitioning the sample into three latent categories is the suitable quantity of latent classes. *Table 3* shows the descriptive statistics when divided into three latent classes.

Table 3 – Descriptive statistics for each latent class when dividing the sample into three latent classes using LCCA

Variable			Class 1(N=111)		Class 2(N=263)		Class 3(N=253)		Whole sample (N=627)	
			Count	Share	Count	Share	Count	Share	Count	Share
Socioeconomic variables	Gender	male	49	44.14%	112	42.59%	130	51.38%	291	46.41%
		female	62	55.86%	151	57.41%	123	48.62%	336	53.59%
	Age	18~30 years old	50	45.05%	121	46.01%	81	32.02%	252	40.19%
		31~45 years old	48	43.24%	118	44.87%	156	61.66%	322	51.36%
		over 46 years old	13	11.71%	24	9.13%	16	6.32%	53	8.45%
	Educational level	high school and below	8	7.21%	4	1.52%	4	1.58%	16	2.55%
		vocational college	24	21.62%	28	10.65%	26	10.28%	78	12.44%
		bachelor's degree and above	79	71.17%	231	87.83%	223	88.14%	533	85.01%
	Profession	student	19	17.12%	15	5.70%	0	0.00%	34	5.42%
		civil servants/public institutions	23	20.72%	23	8.75%	41	16.21%	87	13.88%
		enterprise employees	59	53.15%	214	81.37%	191	75.49%	464	74.00%
		self-employed/freelance	7	6.31%	8	3.04%	16	6.32%	31	4.94%
		other	3	2.70%	3	1.14%	5	1.98%	11	1.75%
	Monthly income	less than 5,000 yuan	27	24.32%	23	8.75%	4	1.58%	54	8.61%
		5,000–10,000 yuan	49	44.14%	106	40.30%	102	40.32%	257	40.99%
		10,000–20,000 yuan	30	27.03%	114	43.35%	123	48.62%	267	42.58%
		more than 20,000 yuan	5	4.50%	20	7.60%	24	9.49%	49	7.81%
	Driving experience	driving experience	87	78.38%	228	86.69%	249	98.42%	564	89.95%
		no driving experience	24	21.62%	35	13.31%	4	1.58%	63	10.05%
	Timing of use	early stage (SAV market share is lower than 20%)	14	12.61%	32	12.17%	72	28.46%	118	18.82%
		mid-term stage (SAV market share is close to 50%)	86	77.48%	217	82.51%	175	69.17%	478	76.24%
		mature stage (SAV market share is greater than 80%)	11	9.91%	14	5.32%	6	2.37%	31	4.94%
Historical travel behaviour	Travel purpose	work/school/official business	91	81.98%	254	96.58%	220	86.96%	565	90.11%
		leisure travel	20	18.02%	9	3.42%	33	13.04%	62	9.89%
	Main travel mode	bus/subway	48	43.24%	262	99.62%	1	0.40%	311	49.60%
		private car	33	29.73%	0	0.00%	242	95.65%	275	43.86%
		bicycle/e-bike	30	27.03%	1	0.38%	10	3.95%	41	6.54%
	Main factors affecting mode choice	travel time	33	29.73%	93	35.36%	117	46.25%	243	38.76%
		travel cost	37	33.33%	114	43.35%	32	12.65%	183	29.19%
		comfort	5	4.50%	7	2.66%	58	22.92%	70	11.16%
		convenience	36	32.43%	49	18.63%	46	18.18%	131	20.89%
	Travel distance	less than 5 kilometres	83	74.77%	1	0.38%	1	0.40%	85	13.56%
		5–10 kilometres	28	25.23%	125	47.53%	117	46.25%	270	43.06%
		10–15 kilometres	0	0.00%	93	35.36%	104	41.11%	197	31.42%
		more than 15 kilometres	0	0.00%	44	16.73%	31	12.25%	75	11.96%
	Travel time	less than 15 minutes	38	34.23%	0	0.00%	7	2.77%	45	7.18%
		15–45 minutes	73	65.77%	145	55.13%	194	76.68%	412	65.71%
		45–60 minutes	0	0.00%	84	31.94%	43	17.00%	127	20.26%
		more than 60 minutes	0	0.00%	34	12.93%	9	3.56%	43	6.86%
	Travel Cost	0–5 yuan	71	63.96%	96	36.50%	6	2.37%	173	27.59%
		5–10 yuan	35	31.53%	132	50.19%	80	31.62%	247	39.39%
		10–20 yuan	2	1.80%	32	12.17%	137	54.15%	171	27.27%
		more than 20 yuan	3	2.70%	3	1.14%	30	11.86%	36	5.74%

The biggest characteristic of the first latent class is short travel distance. 74.77% of the travel distances are shorter than 5 kilometres. At the same time, 63.96% of the samples in the first latent class spent less than 5 yuan when travelling. The first latent class corresponded to what is deemed *short-distance travellers*.

In the second latent class, 99.62% of the samples travel by bus or subway, their travel distance is greater than 5 kilometres, and the travel time is greater than 15 minutes. Therefore, the second class is identified as *non-short-distance PT travellers*.

Similar to the second latent class, 99.60% of the samples in the third latent class have a travel distance greater than 5 kilometres. 97.23% of the sample travel time is longer than 15 minutes. In contrast to the other two classes, this class has a notably higher spending on travel, and 66.01% of them spent more than 10 yuan. 95.65% of the samples travel by private car. Based on the above characteristics, the third latent class is identified as *non-short-distance private car travellers*.

5.2 Confirmatory factor analysis

CFA is developed and estimated for all three latent classes and the whole sample. We select the following indicators [24] to evaluate the CFA model fit (constructive validity): ratio of Chi-square value to the degree of freedom (χ^2,*df*), standardised root mean square residual (SRMR), root mean square error of approximation (RMSEA), comparative fit index (CFI), and Tucker–Lewis index (TLI). The CFA fit indices are detailed in *Table 4*.

Table 4 – Fitness statistics of CFA

Fit indices	Short-distance travellers	Non-short-distance PT travellers	Non-short-distance private car travellers	Whole sample	Recommended value
χ^2,*df*	1.156	1.336	1.644	1.511	<3
SRMR	0.061	0.040	0.048	0.031	<0.08
RMSEA	0.038	0.036	0.051	0.029	≤0.08
CFI	0.979	0.981	0.965	0.988	≥0.9
TLI	0.973	0.975	0.954	0.985	≥0.9

In this study, the following are used as the criteria [25]: χ^2,*df* < 3; SRMR <0.08; RMSEA≤0.08; CFI≥0.9; TLI≥0.9. The fit indices for the three latent classes and the whole sample are all within the recommended values. Therefore, the CFA model fit statistics presented in this study are acceptable.

The tests of internal consistency are undertaken utilising both Cronbach's alpha and composite reliability. An outcome above 0.7 for these metrics indicates good internal consistency [26].

The evaluation of whether various indicators of the same construct concur is known as convergent validity [27]. The factor loading of the manifest indicators (items) should be statistically significant and exceed 0.6 to ensure convergent validity. The convergent validity was also assessed using the average variance extracted (AVE) metric. An AVE above 0.5 is viewed as appropriate.

Table 5 shows the results of the internal consistency tests and the convergent validity tests. All five latent variables have Cronbach's α and CR values surpassing the 0.7 benchmark, which indicates that the internal consistency is acceptable. The manifest indicators' standard coefficients all surpass 0.6 and demonstrate statistical significance at the 0.01 level. All five latent variables have AVEs that exceed the minimum acceptable value of 0.5. This indicates that convergent validity is acceptable.

The results in *Tables 4 and 5* show that the manifest indicators represent the latent variables well. Further analysis can be performed. Selected indicators of manifest indicators are used separately to predict the scores of five psychological latent variables: Perceived Risk, Perceived Usefulness, Perceived Ease of Use, Perceived Trust and Willingness to Use. Latent variable scores are used as explanatory variables in the construction of passengers' travel behaviour model for SAV and bus.

Table 5 – Internal consistency and convergent validity

Class	Latent variables	Items	Factor loading	p-value	AVE	CR	Cronbach'α	Class	Latent variables	Items	Factor loading	p-value	AVE	CR	Cronbach'α
Short-distance travellers	PR	PR1	0.860	0.000	0.663	0.855	0.852	Non-short-distance PT travellers	PR	PR1	0.833	0.000	0.602	0.818	0.807
		PR2	0.755	0.000						PR2	0.671	0.000			
		PR3	0.824	0.000						PR3	0.814	0.000			
	PU	PU1	0.769	0.000	0.521	0.765	0.764		PU	PU1	0.725	0.000	0.509	0.756	0.748
		PU2	0.724	0.000						PU2	0.656	0.000			
		PU3	0.668	0.000						PU3	0.756	0.000			
	PEU	PEU1	0.717	0.000	0.591	0.812	0.808		PEU	PEU1	0.758	0.000	0.542	0.780	0.777
		PEU2	0.832	0.000						PEU2	0.741	0.000			
		PEU3	0.753	0.000						PEU3	0.708	0.000			
	PT	PT1	0.745	0.000	0.537	0.777	0.773		PT	PT1	0.679	0.000	0.557	0.790	0.785
		PT2	0.727	0.000						PT2	0.766	0.000			
		PT3	0.726	0.000						PT3	0.790	0.000			
	WU	WU1	0.789	0.000	0.528	0.769	0.771		WU	WU1	0.685	0.000	0.581	0.805	0.797
		WU2	0.656	0.000						WU2	0.789	0.000			
		WU3	0.728	0.000						WU3	0.806	0.000			
Non-short-distance private car travellers	PR	PR1	0.800	0.000	0.651	0.848	0.846	Whole data	PR	PR1	0.836	0.000	0.638	0.841	0.839
		PR2	0.871	0.000						PR2	0.769	0.000			
		PR3	0.744	0.000						PR3	0.789	0.000			
	PU	PU1	0.879	0.000	0.576	0.801	0.787		PU	PU1	0.801	0.000	0.535	0.774	0.768
		PU2	0.650	0.000						PU2	0.658	0.000			
		PU3	0.730	0.000						PU3	0.728	0.000			
	PEU	PEU1	0.741	0.000	0.542	0.780	0.779		PEU	PEU1	0.746	0.000	0.546	0.783	0.782
		PEU2	0.726	0.000						PEU2	0.751	0.000			
		PEU3	0.741	0.000						PEU3	0.720	0.000			
	PT	PT1	0.714	0.000	0.558	0.791	0.784		PT	PT1	0.719	0.000	0.566	0.796	0.792
		PT2	0.784	0.000						PT2	0.789	0.000			
		PT3	0.741	0.000						PT3	0.748	0.000			
	WU	WU1	0.815	0.000	0.574	0.801	0.805		WU	WU1	0.748	0.000	0.587	0.810	0.807
		WU2	0.770	0.000						WU2	0.777	0.000			
		WU3	0.682	0.000						WU3	0.774	0.000			

5.3 Model estimations results of passengers' travel behaviour for SAV and BUS

Table 6 shows the model estimations results of passengers' travel behaviour for SAV and bus. The significance level used in this study is 0.05. The Halton draws for the mixed Logit model are set at 2,000. Scholarly evidence has demonstrated that Halton draws can offer a more efficient distribution of draws [21]. The log-likelihood values, R-squared and adjusted R-square of the model are also shown in *Table 6*.

Table 6 – Model estimations results of passengers' travel behaviour for SAV and bus

Variable		Short-distance travellers		Non-short-distance PT travellers		Non-short-distance private car travellers		Whole sample	
		Coef.	p-value	Coef.	p-value	Coef.	p-value	Coef.	p-value
Base (bus)	waiting time	-0.058**	0.046	-0.078***	0.000	-0.070***	0.005	-0.055***	0.000
	travel time	--	--	-0.100***	0.000	-0.102***	0.000	-0.074***	0.000
	travel cost	-0.148***	0.006	-0.198***	0.000	-0.154***	0.000	-0.172***	0.000
Gender (base: female)	male	-0.657***	0.007	--	--	-0.405**	0.021	-0.298***	0.002
Age (base: 31 to 45 years old)	18 to 30 years old	0.860**	0.012	--	--	--	--	0.249**	0.018
	over 46 years old	--	--	0.789***	0.009	--	--	0.470**	0.016
Educational level (base: bachelor's degree or above)	high school and below	--	--	NA	NA	NA	NA	--	--
	vocational college	--	--	-0.707**	0.013	--	--	-0.411**	0.011
Profession (base: enterprise employee)	student	--	--	--	--	NA	NA	--	--
	civil servant	--	--	--	--	0.683**	0.015	--	--
	self-employed/ freelance	--	--	--	--	--	--	--	--
	other	NA	NA	NA	NA	NA	NA	--	--
Monthly income (base: 10,000 to 20,000 yuan)	less than 5,000 yuan	--	--	-1.172***	0.008	NA	NA	-0.744***	0.004
	5,000 to 10,000 yuan	--	--	--	--	--	--	-0.275**	0.011
	more than 20,000 yuan	NA	NA	--	--	--	--	--	--
Driving experience (base: no driving experience)	yes	1.239***	0.003	--	--	NA	NA	0.498***	0.008
Timing of use (base: mid-term stage)	early stage	0.935***	0.008	--	--	1.008***	0.000	0.332**	0.015
	maturity stage	--	--	--	--	NA	NA	-1.959***	0.000
Travel purpose (base: work/school/ business travel)	leisure travel	--	--	--	--	--	--	-0.438**	0.012
Main travel mode (Base: bus/subway)	private car	--	--	NA	NA	NA	NA	0.489***	0.000
	bicycle/e-bike	--	--	NA	NA	--	--	--	--
Main factors affecting mode choice (base: travel time)	travel cost	-1.094***	0.002	-1.862***	0.000	-1.861***	0.000	--	--
	comfort	NA	NA	NA	NA	--	--	--	--
	convenience	--	--	-0.584***	0.005	--	--	--	--
Travel distance (base: 5 to 10 kilometres)	less than 5 kilometres	0.515**	0.041	NA	NA	NA	NA	0.414**	0.022
	10 to 15 kilometres	NA	NA	--	--	--	--	-0.282**	0.016
	more than 15 kilometres	NA	NA	--	--	-0.936***	0.004	-0.608***	0.001
Travel time (base: 15 to 45 minutes)	less than 15 minutes	--	--	NA	NA	NA	NA	--	--
	45 to 60 minutes	NA	NA	0.485***	0.010	--	--	--	--
	more than 60 minutes	NA	NA	--	--	--	--	--	--
Travel cost (base: 5 to 10 yuan)	0 to 5 yuan	--	--	-0.661***	0.001	NA	NA	-0.836***	0.000
	10 to 20 yuan	NA	NA	1.133***	0.000	1.022***	0.000	0.932***	0.000
	more than 20 yuan	NA	NA	NA	NA	0.875***	0.006	0.679***	0.003
Latent variables	PR	-0.401**	0.028	-0.232**	0.039	-0.296**	0.012	-0.282***	0.000
	PU	--	--	0.676***	0.000	1.233***	0.000	0.513***	0.000
	PEU	--	--	--	--	--	--	--	--
	PT	--	--	0.288**	0.041	--	--	--	--
	WU	1.040***	0.006	--	--	--	--	0.337**	0.046
Random parameters	NsWTIME	--	--	--	--	0.099**	0.032	0.066**	0.017
Log-likelihood		-305.816		-661.466		-601.838		-1662.137	
R-sqrd		0.205		0.274		0.314		0.235	
R2Adj		0.177		0.257		0.299		0.226	

Note: (1) Significance level: ***p≤0.01, **p≤0.05. (2)-- = the results are not statistically significant at the 5% level, and the ultimate model excludes variables that are not significant. (3) NA = small sample size, not applicable in the model.

From the model results, it can be seen that LCCA can reduce heterogeneity to a certain extent. The waiting time in the *whole sample* is a random parameter with a normal distribution of (-0.055, 0.066^2). While other distributions such as lognormal, uniform, exponential and Weibull were assessed for statistical significance, they did not exhibit superior performance compared to the normal distribution. This parameter shows that in the *whole sample*, as the SAV waiting time increases, 79.67% of passengers will decrease their probability of choosing SAV and choose bus instead. Conversely, 20.33% of the passengers will not behave like this. After using LCCA, only the waiting time in *non-short-distance private car travellers* is a random parameter, which obeys the normal distribution of (-0.070, 0.099^2). The waiting time for *short-distance travellers* and *non-short-distance PT travellers* becomes a fixed parameter. Among *short-distance travellers* and *non-short-distance PT travellers*, with the increase of SAV waiting time, the probability of all passengers choosing SAV will decrease, and they will choose bus instead. In *non-short-distance private car travellers*, with the increase of SAV waiting time, 76.11% of passengers will decrease the probability of choosing SAV and choose bus instead, while 23.89% of passengers will not.

In *non-short-distance PT travellers*, *non-short-distance private car travellers* and *whole sample*, as the SAV travel time increases, the probability of passengers choosing SAV will decrease and they will choose bus instead. Travel time is not significant in *short-distance travellers* (the coefficient value for travel time in *short-distance travellers* is -0.037, the p-value is 0.094, and the significance level used in this study is 0.05). Travel cost is significant in all classes. As SAV travel cost increases, the probability of passengers choosing SAV will decrease and they will choose bus instead.

Perceived Risk is significant in each group. As the perceived risk score increases, passengers are less likely to choose SAV and choose bus instead. Perceived Usefulness is significant in *non-short-distance PT travellers*, *non-short-distance private car travellers* and *whole sample*. As the Perceived Usefulness score increases, the probability of passengers in these classes choosing SAV increases. Perceived Ease of Use is not significant in all classes. Perceived Trust is only significant in *non-short-distance PT travellers*, and as the Perceived Trust score increases, the likelihood of passengers in this class choosing SAV increases. Willingness to Use is significant in *short-distance travellers* and *whole sample*. As the score of Willingness to Use increases, the possibility of such passengers choosing SAV will increase.

5.4 Marginal effects

Table 7 shows the marginal effects of service attributes. We calculated the marginal effects of the service attributes (waiting time, travel time and travel cost) for SAV and bus at the mean value of each class of sample.

Table 7 – Marginal effects

Mode	Changing variable	Value added	Probability change value of transportation mode choice							
			Short-distance travellers		Non-short-distance PT travellers		Non-short-distance private car travellers		Whole sample	
			SAV	bus	SAV	bus	SAV	bus	SAV	bus
SAV	waiting time	1 min	-0.0522	0.0522	-0.064	0.064	-0.0367	0.0367	-0.0445	0.0445
	travel time	1 min	-0.1367	0.1367	-0.3191	0.3191	-0.283	0.283	-0.2516	0.2516
	travel cost	1 yuan	-0.4178	0.4178	-0.4865	0.4865	-0.336	0.336	-0.4523	0.4523
bus	waiting time	1 min	0.1574	-0.1574	0.1815	-0.1815	0.0895	-0.0895	0.1235	-0.1235
	travel time	1 min	0.2594	-0.2594	0.6092	-0.6092	0.5319	-0.5319	0.4787	-0.4787
	travel cost	1 yuan	0.0799	-0.0799	0.0906	-0.0906	0.0613	-0.0613	0.0836	-0.0836

Note: There are only two modes of transportation to choose from in the model, so the probability value of a decrease in one mode is the probability value of an increase in the other mode.

It can be seen from the marginal effects that among the three classes of passengers, *non-short-distance PT travellers* are most sensitive (the probability experiences the most significant change when there is an increase of one unit in the service attribute) to waiting time, travel time and travel costs. This means that this class of passengers is most likely to be affected by service attributes. *Short-distance travellers* are the least sensitive to travel time. *Non-short-distance private car travellers* are the least sensitive to wait times and travel costs.

6. DISCUSSION AND CONCLUSIONS

This paper focuses on passengers' travel behaviour for SAV and bus. We have divided passengers into three classes through LCCA, namely *short-distance travellers, non-short-distance PT travellers* and *non-short-distance private car travellers*. Different classes of travellers exhibit different travel preferences. The travel time of *short-distance travellers* is not significant (the coefficient value is -0.037, the p-value is 0.094, the p-value is greater than 0.05 and lower than 0.1). At the same time, the marginal effects value of travel time in this class are also significantly lower compared to the other two classes. This means that *short-distance travellers* do not pay much attention to travel time. This may be due to spending less time in transit due to short distance. *Non-short-distance PT travellers* are most likely to be affected by service attributes. Compared with the other two classes of passengers, *non-short-distance PT travellers* are most sensitive to waiting time, travel time and travel costs. Increases in waiting time, travel time and travel cost can easily lead them to choose other modes. Similarly, reductions in waiting time, travel time and travel cost can easily attract them. There is still some heterogeneity among *non-short-distance private car travellers.* Some passengers in this class will choose bus because of increased SAV waiting time, while others will still choose SAV despite that. This suggests that there are passengers in this class that prioritise factors beyond service attributes, such as comfort.

It is worth noting that among *non-short-distance PT travellers*, those who primarily consider convenience when travelling are more willing to choose the bus than those who primarily consider travel time. This means that some travellers feel that the SAV appointment process is cumbersome and causes them to choose the bus. The SAV appointment process of is as simple as possible to avoid being affected by cumbersome elements.

Perceived Risk is a significant variable in all classes, indicating that safety considerations (device security, system security, privacy security) are the most important factor for travellers. Improving SAV safety is a factor driving effective passenger acceptance of SAV. Zhang et al. [28] pointed out that Perceived Risk does not determine passengers' attitudes towards autonomous driving directly, but rather indirectly by affecting passengers' Perceived Trust in autonomous driving. Unlike Perceived Risk, which is significant in every class, Perceived Trust is only significant among *non-short-distance PT travellers.* This shows that passengers still lack trust in SAV. When promoting SAVs, special attention should be paid to improving passengers' awareness of autonomous driving technology to improve Perceived Trust and reduce potential Perceived Risk.

People who travel short distances may prefer to opt for SAV. Through the significance of the travel distance item in the model, it can be found that the possibility of choosing a bus increases significantly after the distance increases. This is consistent with the findings of Liu et al. [29] and Nazari et al. [6]. Liu et al. found that passengers travelling short distances are more likely to choose SAV, while those travelling longer distances prefer to take the bus to enjoy lower travel costs. Nazari et al. observed that people with a higher daily mileage do not prefer to use SAV for their daily commute. In *short-distance travellers*, people whose travel distance is less than five kilometres are more inclined to choose SAV. At the same time, the Willingness to Use score of *short-distance travellers* is a significant variable, and the coefficient value is positive. The above results show that passengers travelling short distances may be more willing to choose SAV. Moreover, the first and last mile of public transportation is also a type of short-distance travel, which means that SAV has the potential to be used as a first and last mile travel mode.

Judging from the proportion of the timing of use, *non-short-distance private car travellers* are more likely to become early SAV adopters. From the above analysis, we can deduce that SAV could be a potential mode for short-distance transportation. This means that after SAV is put on the market, different promotion strategies should be adopted in different application stages. In the early stage, the SAV customer focus should be on *non-short-distance private car travellers*. After SAV has achieved a certain market share and popularity, it should focus on first and last mile to realise the coordinated development of SAV and public transport.

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王亚宁，霍月英，张学斌

考虑异质性的共享自动驾驶汽车和常规公交乘客出行行为建模：中国北京和上海的案例研究

摘要

自动驾驶汽车的普及会产生一种新的商业模式，被称为共享自动驾驶汽车（SAV），SAV可能会吸引大量出行者从而导致常规公交分担率的下降，这可以通过探究乘客在面对SAV和常规公交的方式选择行为来解释，因此本文对SAV和常规公交的出行行为进行研究，旨在探讨影响乘客出行行为的因素，揭示SAV乘客的出行特征。我们使用潜在类别聚类分析对乘客进行分类，并基于验证性因子分析和混合Logit模型对乘客的出行行为进行建模。研究结果表明，不同类的出行者的出行偏好存在异质性，短途出行者不太关注出行时间，非短途公交出行者最有可能受到出行方式属性（等待时间、出行时间和出行费用）的影响，非短途私家车出行者更有可能成为SAV的早期采用者。短途出行的乘客更有可能选择SAV，这揭示了SAV作为公共交通最后一公里接驳的潜力，研究还发现乘客对SAV缺乏信任，会影响SAV的推广。

关键字

共享自动驾驶汽车；常规公交；方式选择行为；异质性；混合Logit模型。