Latent Attitudes of Existing Travel Modes on Autonomous Vehicle Adoption

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ABSTRACT

With the quick advance of autonomous vehicle (AV) technology, understanding the potential demand of AV and its user characteristics has increasingly become a popular area of research. In consumer choice and technology adoption literature, whenever the demand of a new product is forecasted, the attitudes towards existing choices are found important in addition to new product attributes and consumer characteristics. While there is an abundance of literature from stated preference (SP) surveys identifying attitudes are just as important as demographics in forming a purchase or usage decision of AVs, past studies have seldom looked at how attitudes towards existing travel modes affect the new mode adoption. We conduct a dynamic online SP survey in Singapore on 2,003 individuals, with indicator questions about impressions on existing modes. We focus on how these attitudes affect AV adoption based on confirmatory factor analysis and discrete choice models with latent variables. The results show that having positive attitudes towards public transit casts a negative effect on AV adoption, while having positive attitudes towards ridesharing is positive on AV adoption. And, positive attitudes towards walking and driving do not have any significant effects. In addition, the model identifies that highly educated, wealthy, and/or younger people as the population to have more positive attitudes towards new technologies and more likely to adopt AVs. The research provides insights on potential relationship between AVs and existing modes, as well as the characteristics of potential audience, which may be of help in planning future AV services.

Keywords: Autonomous Vehicles, Choice Behavior, Discrete Choice Methods, Factor Analysis, Latent Variables

INTRODUCTION

Autonomous vehicles (AV) are at the center of the discussion of human mobility all over the world. With the advent of more advanced sensing and processing capabilities, humans have reached level 4 autonomy and the best AV can drive more than 11,000 miles without human intervention (*1*). Although there is still a long way to go before we could see fully autonomous vehicles on the street, the future is more within reach than ever.

Not only is the driving technology facing a revolution, but also the whole transportation network (*2*–*5*). For an innovative technology as disruptive as AV, it is important to understand the public's reactions, the potential demand, and impact to the existing network, in order to draw the most benefits and mitigate the potential disruptions. This study focuses on demand analysis of AVs using a stated preference survey. AV demand analysis is different from traditional travel demand models in that AV is a new technology. Theories for technology adoption emphasizing people's perceptions and attitudes are applicable. In addition, AV demand analysis fits into the traditional travel demand model framework, since most of the existing demand is already realized by other modes. Researchers have studied the influence of different attitudes on AV adoption, such as risk preference (*6*), trust, environmental concerns (*7*), technology enthusiasm, and attitudes towards AV itself (*8*), etc. Past studies, however, have seldom looked at the attitudes towards how current travel modes influence AV adoption. In this study, we borrow ideas from technology adoption, brand loyalty (*9*, *10*), and discrete choice models to analyze potential substitution patterns between different travel modes with respect to AVs and how the attitudes towards existing travel modes influence AV adoption.

The rest of this paper is organized as follows. Section 2 reviews existing literature on demand analysis, paying special attention to the consideration of attitudinal variables, as well as literature on how attitudes about existing choice (loyalty) affect choices and technology adoption. Section 3 discusses survey designed to verify our hypothesis and the surveyed demographics. Section 4 provides the details on our model formulation and the results are presented and analyzed in Section 5. Finally, findings are summarized, and the limitations and potential for future studies are discussed in Section 6.

LITERATURE REVIEW

Literature on the demand analysis of AVs starts to emerge in the past five years. Gkartzonikas and Gkritza (*11*) provide a comprehensive review on the efforts to characterize potential AV user preference/behaviors. Most studies use descriptive statistical analyses and regression methods to identify socioeconomic, travel characteristics, and attitudes of individuals affecting AV adoption choices (*12*–*16*). Among current literature, recurring attitudinal factors found to affect behavioral intentions of AV adoption are: level of awareness of AVs; consumer innovativeness; safety; trust of strangers; environmental concerns; relative advantage, compatibility and complexity; subjective norms; self-efficacy; and driving-related seeking scale.

In addition to understanding what influences AV adoption, researchers attempt to build models to forecast potential market share and demand of AVs. The state-of-the-art method for mode choice is mixed logit models with trip characteristics, socioeconomic variables, and attitudinal latent class/variables. Several models are developed to answer different research questions regarding AV demand. Daziano et al. (*17*) adopt a mixed logit formulation with demographics to explore the heterogeneity in preference and willingness to pay for AVs. Yap et al. investigate the competitiveness of AVs as an egress mode for last-mile access from public transport multi-modal trips, and identify trust and sustainability as the most influential attitudinal variables (*7*). Haboucha et al. (*8*) identify five latent variables—technology interest, environmental concern, enjoy driving, public transit attitude, and pro-AV sentiments—to study the long-term choice decisions regarding owning and using AVs, and find that the Israelis have a more welcoming attitude for AV than the Americans. All the attitudinal variables investigated so far are either concentrated on the individual characteristics, or having individual characteristics mixed in with attitudes towards current modes.

We also draw insights from another body of choice literature: marketing. Researchers and companies have been looking into what influences consumers purchasing behavior. And brand loyalty has been identified and studied as an important factor. There are two approaches towards loyalty: behavioral and attitudinal, where behavioral loyalty is maintained when customers keep purchasing the brand and attitudinal loyalty refers to the good will of the brand (*9*). They are highly correlated (*10*). In earlier studies, attitude is usually measured through instruments such as past purchasing behavior (*18*). Purchasing behavior is nonetheless not an ideal instrument, since there are other factors influencing purchasing behavior, and the attitudinal part cannot be represented. In the transportation context, only about half of the people travel with their preferred mode (*19*). More recent literature uses factor models or principal component analysis to measure loyalty, which has the potential to incorporate both the behavioral and attitudinal aspect of loyalty (*9*, *20*). In our context, since people are travelling with other modes until AV enters the market, and AV is about to seize the market of other modes. The situation is analogous to brands competing with new products; therefore, we hypothesize the attitudes towards existing modes will play a factor in whether an individual will make a switch when everything else (time, cost, etc.) is held equal.

However, brand loyalty is not entirely applicable to AV adoption since AV is a new mode that people are not familiar with. The most widely cited model in the field of technology acceptance—the technology acceptance model—explains the motivation behind technology acceptance by perceived usefulness, perceived ease of use, and attitude towards use. Along with other models in the realm of technology acceptance, user perception and attitude are emphasized (*21*). Since AV is not yet available, the answers we get from asking indicator questions on AV would be unreliable at best. And the definition of 'pro-AV' sentiment itself is vague without everybody having the same definition of how a future with AV looks like. Some have tried to use individual traits like risk preference to characterize this perception (*6*). In this study, we focus on the influence of the respondents' attitudes of existing modes on their stated choice.

SURVEY DESIGN AND DATA

This study tries to incorporate people's attitudes towards existing travel modes into AV's mode choice forecast using stated preference survey conducted in Singapore. Singapore is a leader in the world of adopting new transport technologies and experimenting with different policy regulations and it aims to be one of the first markets to adopt AVs if they become commercially available. It is valuable to understand who is more likely to use AVs and the potential demand in Singapore.

In this study, we conducted a dynamic online stated preference (SP) survey in Singapore in July 2017 via Qualtrics platform with 2,003 valid responses collected. We specifically asked for the respondents' perceptions of current modes through a series of indicator questions to investigate the relationship between AVs and other modes in terms of user perception.

Survey Design

The survey consists of three parts: revealed preference (RP), stated preference, and socioeconomic information. A flow diagram illustrating the process is shown in Figure 1. The RP part collects information on the respondent's origin and destination postal codes, and current travel mode. Different from traditional survey designs, this is a web-based dynamic survey that computes some trip-specific characteristics based on respondents' initial response of original and destination postal codes. Bus travel cost, bus waiting time, ride hailing waiting time are held constant at the market average and walking time, bus access walking time, bus in-vehicle time, ride hailing travel cost, and ride hailing in-vehicle time are calculated specific to their origin/destination responses.

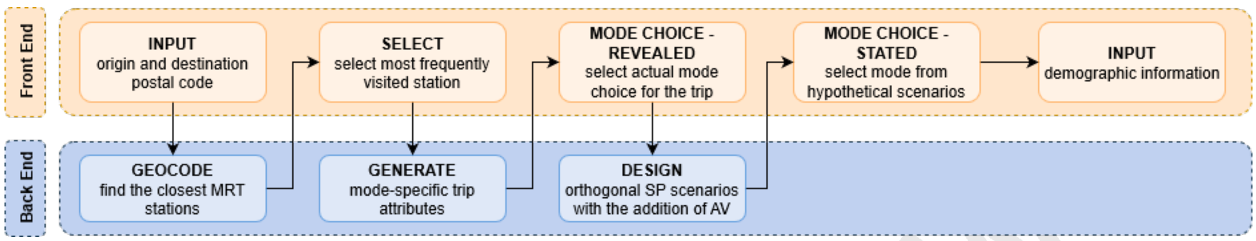

FIGURE 1 Survey Process Flow Diagram

The second part is SP. Based on the locations indicated in the first part, hypothetical trip scenarios are generated, and AV is added as an option. In this survey, the form of AV deployment considered is a fleet-based mobility service with trip attributes similar to those of ride hailing, since this is the form of deployment to be piloted in Singapore (*22*). This part of the survey follows the standard orthogonal survey design, as unbiasedness comes before efficiency, especially when we do not have a prior belief what the response is going to be. Each attribute has three levels of values with the median anchored to the one calculated in RP, so that the respondents will provide the most realistic choices. The final SP survey has 54 combinations of attribute values, and each respondent is given 7 at random. A sample interface is shown below in Figure 2.

	Total Cost	Origin	Walk (min)	Wait (min)	In-vehicle (min)	Destin.	Total Time
1. Walk	$0.0		30	n.a.	n.a.		30 min
2. Bus	$1.3		4	5	18		27 min
3. Ride Hailing	$4.0		n.a.	3	12		15 min
4. Ride Hailing with AV	$5.0		n.a.	3	8		11 min
5. Drive	$4.0		3	n.a.	9		12 min

FIGURE 2 State Preference Sample Interface

Besides collecting mode choice, indicator questions that measures attitudes towards different modes are asked. A couple studies have looked at the indicators that could measure latent attitudes towards travel modes (*23*, *24*) and we select four indicators regarding different aspects of travel (reliability, easiness to use, safety, comfort) and an overall impression for each mode so that the respondents draw comparisons between the modes while answering ranking the choices. Using a 7-point Likert scale, the respondents indicate their attitudes, ranging from "totally disagree" to "totally agree". The indicators used in the survey are listed in Table 1.

In the last part, the socioeconomic information of the respondents is collected, including gender, ethnicity, employment, age, education, income, auto ownership, and license ownership.

TABLE 1 Indicators used in factor analysis of attitudes

Indicator		Question
Pro-walk (Indicators W)	Walk safe	I think walking feels safe.
	Walk comfortable	I think walking is comfortable.
	Walk reliable	I think walking is a reliable mode.
	Walk easy	I think walking feels easy.
	Walk overall	I enjoy walking.
Pro-PT (Indicators P)	PT safe	I think taking public transport feels safe.
	PT comfortable	I think taking public transport is comfortable.
	PT reliable	I think public transport is a reliable mode.
	PT easy	I think taking public transport is easy.
	PT overall	I enjoy taking public transport.
Pro-RH (Indicators R)	RH safe	I think ride hailing feels safe.
	RH comfortable	I think ride hailing is comfortable.
	RH reliable	I think ride hailing is a reliable mode.
	RH easy	I think ride hailing is easy.
	RH overall	I enjoy ride hailing.
Pro-Drive (Indicators D)	Drive safe	I think driving feels safe.
	Drive comfortable	I think driving is comfortable.
	Drive reliable	I think driving is a reliable mode.
	Drive easy	I think driving is easy.
	Drive overall	I enjoy driving.

Sample Representativeness

We compare the shares of gender, age, and employment in our sample to the Household Interview Travel Survey (HITS) conducted in 2012, the most recent official statistics of household travel information. The HITS collects trip-level attributes as well as individual demographics, targeting a sample size of over 10,000 households, about 1% of the total number of households in Singapore. The sampled households are randomly selected to ensure the representativeness of population. For income, we use published income report from the Department of Statistics (*25*) to measure our sample representativeness. Although our sample is quite not exactly the same with the population, representations in each category is enough so that parameter estimation is not affected.

TABLE 2 Survey sample demographics

Characteristics	Level	Sample (%)	Population (%)
Gender	Male	53.8	46.5
Age	18 – 24	13.9	11.4
	25 – 34	27.2	19.1
	35 – 44	23.5	19.0
	45 – 54	21.2	18.4
	55 and older	14.1	32.0
Income (monthly)	Less than S$2,000	10.0	18.3
	S$2,000 – S$3,999	15.2	10.7
	S$4,000 – S$5,999	15.7	11.3
	S$6,000 – S$7,999	15.8	10.9
	S$8,000 – S$9,999	14.0	9.5

	S$10,000 – S$11,999	10.8	8.4
	S$12,000 – S$14,999	4.7	9.1
	S$15000 – S$19,999	8.7	9.5
	S$20,000 and above	5.0	12.4
Employment	Full Time	69.1	46.0
	Part Time	7.4	3.33
	Unemployed looking for work	7.9	2.85
	Retired	3.7	10.8
	Student	8.2	9.24
	Other	3.7	2.78

MODEL SPECIFICATION

We adopt a latent variable discrete choice model to measure the impact of people's attitudes toward previous travel modes on the adoption of a new technology—AV. The latent variable model allows the researchers to estimate latent constructs from a series of observed indicators and establish the validity of the latent variables. In this study, we estimate four latent factors with respect to existing modes—*i.e.* pro-walk, pro-PT, pro-RH and pro-drive—and explore their relations with key behavioral outcomes of interest. First, a measurement model is estimated to establish the validity of four latent attitudes regarding previous modes. Second, a latent variable discrete choice model is formulated to quantify the latent attitudes and their impacts on travel mode choice with the introduction of AV.

Measurement Model

A confirmatory factor analysis (CFA) model is estimated to identify a reliable measure of four latent attitudes of previous travel modes. We compare the overall model fit to established standards: a χ^2 test statistic that is not statistically different from zero, comparative fit index (CFI) and Tucker-Lewis index (TLI) greater than 0.90, and root mean square error of approximation (RMSEA) and standardized root mean square residual (SRMR) less than 0.08 (*26*, *27*). We demonstrate the convergent validity of four latent attitudes by showing that all items have standardized factor loadings over 0.5, suggesting that the majority of the variation in the response patterns on the observed indicators is explained by our pre-assumed latent constructs (*28*). The measurement model is estimated in R programming language (*29*) with maximum likelihood estimation. We standardized the latent factors to allow for free estimation of all factor loadings.

Latent Variable Model

Latent attitudes are reflected by people's responses to indicator questions and are characterized by people's sociodemographic information. Therefore, we formulate the latent variable model as an ordinal logit model with psychometric indicators as dependent variables. Denote the m^{th} latent attitude of individual n as A_{nm}. Then we have

$$A_{nm} = \theta_{0m} + \boldsymbol{\theta_{Xm}} \boldsymbol{X_n} + \eta_m, \tag{1}$$

where θ_{0m} is the intercept; $\boldsymbol{X_n}$ is the vector of sociodemographic variables of individual n used for latent attitude estimation; $\boldsymbol{\theta_{Xm}}$ is the coefficients of the sociodemographic variables with respect to the m^{th} latent attitude; and $\eta_m \sim \mathcal{N}(0, \sigma_{Am})$ is a normally distributed error term for the m^{th} latent attitude. As the measurements are made using a Likert scale with 7 levels, we define 6 parameters τ_{im} (i=1,2…,6) for each latent attitude m. To account for the symmetry of the indicators, we define three positive parameters δ_{1m}, δ_{2m} and δ_{3m}, such that

$$\begin{cases} \tau_{1m} = -\delta_{1m} - \delta_{2m} - \delta_{3m} \\ \tau_{2m} = -\delta_{1m} - \delta_{2m} \\ \tau_{3m} = -\delta_{1m} \\ \tau_{4m} = \delta_{1m} \\ \tau_{5m} = \delta_{1m} + \delta_{2m} \\ \tau_{6m} = \delta_{1m} + \delta_{2m} + \delta_{3m} \end{cases} \tag{2}$$

Also, we define the utility in the ordinal logit model for individual n towards indicator k with respect to latent attitude m as Z_{nmk}. We have

$$Z_{nmk} = \lambda_{0mk} + \lambda_{Amk} A_{nm} + v_{mk}, \tag{3}$$

where λ_{0mk} is the intercept; λ_{Amk} is the coefficients for latent attitudes; and $v_{mk} \sim \mathcal{N}(0, \sigma_{Zm})$ is the error term. Therefore, the probability of a given response to an indicator question $I_{nmk} = i$ (i=1….7) is given by:

$$\begin{aligned} \Pr(I_{nmk} = i) &= \Pr\left(\tau_{(i-1)m} \leq Z_{nmk} \leq \tau_{im}\right) \\ &= \Phi\left(\frac{\tau_{im} - \lambda_{0mk} - \lambda_{Amk}(\theta_{m0} + \boldsymbol{\theta_m X_n})}{\sqrt{(\lambda_{Amk}\sigma_{Am})^2 + \sigma_{Zm}^2}}\right) - \Phi\left(\frac{\tau_{(i-1)m} - \lambda_{0mk} - \lambda_{Amk}(\theta_{0m} + \boldsymbol{\theta_m X_n})}{\sqrt{(\lambda_{Amk}\sigma_{Am})^2 + \sigma_{Zm}^2}}\right), \end{aligned} \tag{4}$$

where $\Phi(\cdot)$ is the cumulative distribution function of the standard normal distribution. Note that σ_{Am} and σ_{Zm} cannot both be identified since they are coupled. We replace $\sqrt{(\lambda_{Amk}\sigma_{Am})^2 + \sigma_{Zm}^2}$ with σ_m^* and only estimate σ_m^* for the latent variable model.

Choice Model

Available choice set in the survey includes walking, public transport, ridesharing, AV and driving. Driving is only available to an individual who owns a driver's license. Utilities of the alternatives consist of alternative-specific trip attributes, individual characteristics, and latent attitudes. The utility of individual n towards the mode j, U_{nj}, is defined by

$$\begin{aligned} U_{nj} = V_{nj} + \varepsilon_j &= \beta_{0j} + \boldsymbol{\beta_{Xj} X'_n} + \boldsymbol{\beta_{Tj} T_{nj}} + \sum_{m=1}^{M} \beta_{Amj} A_{nm} + \varepsilon_j \\ &= \beta_{0j} + \boldsymbol{\beta_{Xj} X'_n} + \boldsymbol{\beta_{Tj} T_{nj}} + \sum_{m=1}^{M} \beta_{Amj}(\theta_{0m} + \boldsymbol{\theta_{Xm} X_n} + \eta_m) + \varepsilon_j \\ &= \beta_{0j} + \boldsymbol{\beta_{Xj} X'_n} + \boldsymbol{\beta_{Tj} T_{nj}} + \sum_{m=1}^{M} \beta_{Amj}(\theta_{0m} + \boldsymbol{\theta_{Xm} X_n}) + \tilde{\eta}_j + \varepsilon_j, \end{aligned} \tag{5}$$

where β_{0j} is the alternative specific constants; $\boldsymbol{X'_n}$ is the socioeconomic variables of individual n used in choice model; $\boldsymbol{T_{ni}}$ is the attributes of mode j; $\boldsymbol{\beta_{Xj}}$, $\boldsymbol{\beta_{Tj}}$ and $\boldsymbol{\beta_{Amj}}$ are the corresponding coefficients to estimate; $\boldsymbol{M}$ is the total number of latent attitudes; ε_j is the Gumbel distributed error term. Since we consider both the RP and SP data, the scales of ε_j are different for RP and SP. We normalize the scale of RP data (μ_{RP}) to 1 and denote the scale of SP data as μ_{SP}, which will be estimated in the model. $\tilde{\eta}_j$ is the aggregated error term with normal distribution $N(0, \tilde{\sigma}_j{}^2 = \sum_{m=1}^{M}(\beta_{Amj}\sigma_{Am})^2)$. Thus, the probability for individual n choosing mode j can be expressed by the following equation:

$$\Pr(Y_n = j) = \int \Pr\left(Y_n = j \mid \tilde{\eta}_j\right) \phi\left(\tilde{\eta}_j\right) d\tilde{\eta}_j = \int \frac{\exp(\mu V_{nj})}{\sum_{j'=1}^{5} \exp\left(\mu V_{nj'}\right)} \phi\left(\tilde{\eta}_j\right) d\tilde{\eta}_j, \tag{6}$$

where $\phi(\cdot)$ is the probability density function of the univariate standard normal distribution. μ is the scale of ε_j. $\mu = \mu_{RP} = 1$ for RP questions and $\mu = \mu_{SP}$ (to be estimated) for SP responses.

Model Estimation

The likelihood function can be written as a combination of a latent variable model and a discrete choice model:

$$L(\boldsymbol{\theta},\boldsymbol{\beta},\boldsymbol{\lambda},\boldsymbol{\sigma},\boldsymbol{\delta},\mu_{SP}) = \prod\nolimits_{n=1}^{N} \Pr(Y_n)\cdot\prod_{m=1}^{M}\prod\nolimits_{k\in I(m)}\Pr(I_{nmk})\,, \tag{7}$$

where $\boldsymbol{\theta}, \boldsymbol{\beta}, \boldsymbol{\lambda}, \boldsymbol{\sigma}, \boldsymbol{\delta}$ and $\boldsymbol{\mu_{SP}}$ are the coefficients to be estimated. $I(m)$ is the set of indicators for latent attitude m (see Table 1). For example, for "pro-drive" attitude (m=4), we have $I(m) = \{\text{drive safe, drive comfortable, drive reliable, drive easy, drive overall}\}$. There is no closed form solution for the likelihood function. Simulation-based maximum likelihood estimation is used for estimation. In addition, simultaneously estimating all parameters is computationally difficult. Sequential estimation is a conventional alternative for the model estimation (*7*, *8*, *30*), though the sequential estimation is consistent but inefficient compared with simultaneous estimation. In this study, we estimate the latent variables model first to obtain $\boldsymbol{\theta}, \boldsymbol{\lambda}, \boldsymbol{\delta}$ and $\boldsymbol{\sigma}_{\boldsymbol{m}}^{*}$. Then we fixed these parameters and estimate the choice model for $\boldsymbol{\beta}, \widetilde{\boldsymbol{\sigma}}_{\boldsymbol{j}}$ and $\boldsymbol{\mu_{SP}}$.

A multinomial logit model without latent attitudes is set as the base model for comparison. The models are estimated using PandasBiogeme with 2,000 random draws (*31*).

MODEL RESULTS

Measurement Model

Our survey contains 5 indicator questions for each mode designed to capture passengers' attitudes of previous travel modes. It is intuitive to group the questions about one mode into one factor, which results in four attitudes: pro-walk, pro-PT, pro-RH and pro-drive. We estimate a four-factor CFA model with every 4 items loading onto one factor. The correlation among all latent factors are introduced. The proposed CFA model diagram is depicted in Figure 3.

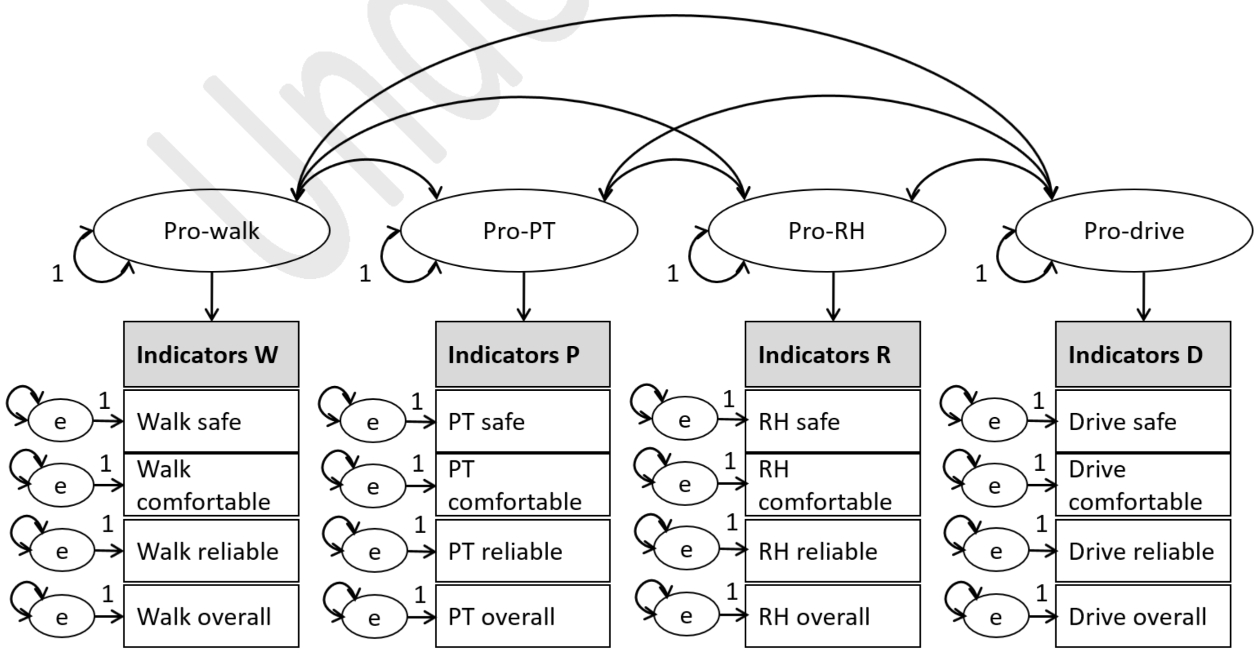

FIGURE 3 Confirmatory Factor Analysis Model Structure

The CFA results are listed in Table 3. We find that this four-item four-factor measure of previous modes attitudes meets established standards of model fit. Given the large sample size, we overlook the statistically significant χ^2 test statistic and note that the CFI and TLI are above the established threshold of 0.90 for moderate model fit. The RMSEA is slightly beyond the threshold but SRMR is well below 0.08 (*26*, *27*). The convergent validity of the measure is also well established, with nearly all indicators having standardized factor loadings beyond 0.5. This suggests that the latent variable of four modes attitudes of the variance in the response patterns to each of the 6 items that constitute the measure.

TABLE 3 Confirmatory Factor Analysis Results

Latent Factor	Indicator	B	SE	Beta	Significance
Pro-walk	Walk safe	0.647	0.028	0.522	***
	Walk comfortable	1.132	0.037	0.637	***
	Walk reliable	0.871	0.027	0.673	***
	Walk easy	1.243	0.034	0.727	***
	Walk overall	1.242	0.028	0.849	***
Pro-PT	PT safe	0.440	0.020	0.490	***
	PT comfortable	0.901	0.028	0.659	***
	PT reliable	0.944	0.026	0.737	***
	PT easy	0.806	0.023	0.701	***
	PT overall	1.042	0.024	0.835	***
Pro-RH	RH safe	0.703	0.020	0.668	***
	RH comfortable	0.801	0.021	0.740	***
	RH reliable	0.802	0.020	0.779	***
	RH easy	0.816	0.022	0.746	***
	RH overall	0.803	0.019	0.795	***
Pro-drive	Drive safe	3.272	0.052	0.988	***
	Drive comfortable	3.545	0.055	0.993	***
	Drive reliable	3.564	0.056	0.994	***
	Drive easy	3.559	0.056	0.994	***
	Drive overall	3.510	0.055	0.994	***
Test Statistics					
$\chi^2(164, N = 2{,}003)$	4111.340 (p<0.001)				
CFI	0.915				
TLI	0.901				
RMSEA	0.109				
SRMR	0.065				

***: p-value < 0.01.

There are also significant correlations between all four latent factors (Table 4). There are positive correlations between walk and PT, as well as between PT and RH. The positive correlations indicate that the modes share some similarities such that people who prefer one would be more likely to prefer the other. Pro-drive does not correlate with attitudes towards other modes, suggesting that perceptions/attitudes associated with driving in Singapore is very different from those of other modes. One possible reason for this phenomenon is the high costs of owning a car and low car ownership in this city (*32*).

TABLE 4 Latent Attitudes Correlation

Factor 1	Factor 2	Correlation	Significance
Pro-walk	Pro-PT	0.606	***
Pro-walk	Pro-RH	0.264	***
Pro-walk	Pro-drive	-0.018	***
Pro-PT	Pro-RH	0.531	***
Pro-PT	Pro-drive	-0.092	***
Pro-RH	Pro-drive	-0.066	***

***: p-value < 0.01.

Latent-variable Discrete Choice Model

Having established a reliable four-dimensional measure of existing modes attitudes, we estimate a latent-variable discrete choice model exploring the impact of AV. The high-level model structure is shown in Figure 4, consisting of two components: a latent variable model and a discrete choice model. Observed variables such as explanatory variables, psychometric indicators, and mode choices are represented by rectangular boxes and latent variables such as utilities, attitudinal variables, and classes are represented by ovals. Structural equations are represented by straight arrows while measurement equations are represented by dashed arrows.

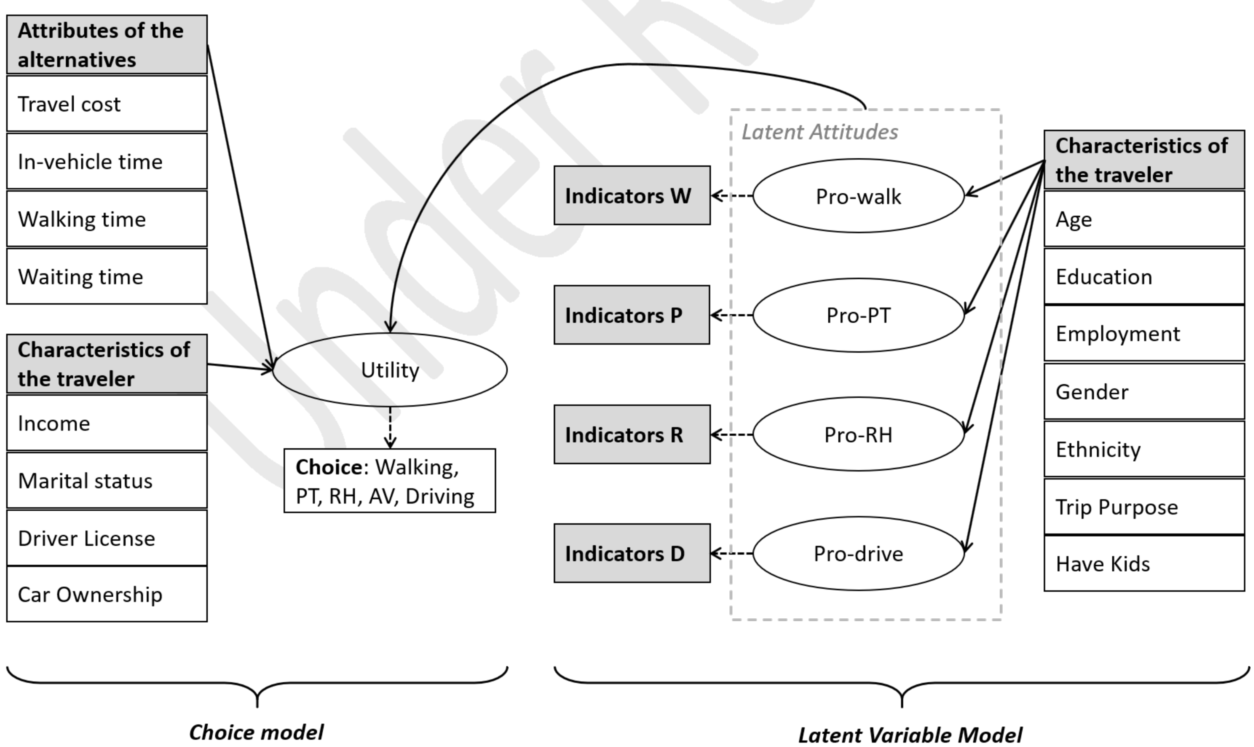

FIGURE 4 Discrete Choice Model Structure with Latent Variable

In order to classify the socioeconomic variables with direct impacts (to be included in choice model) and those with indirect impacts (to be included in latent variable model), we first estimate a latent variable model and a choice model separately, each of which includes all sociodemographic variables. We then assign each variable according to its significance. The assignment of variables for model specification are shown in Figure 4.

The estimates of the latent-variable discrete choice model are illustrated in Table 5. The parameters being estimated are:

1. $\boldsymbol{\lambda_{0mk}}$ are indicator-specific constants, corrects each indicator to the same numerical intervals for ordinal logit.
2. $\boldsymbol{\lambda_{Amk}}$ are contributions of latent attitude to respective indicator choice.
3. $\boldsymbol{\theta}$ are the loadings of socioeconomic variables onto attitudes.
4. $\boldsymbol{\beta_0}$ are alternative-specific constants.
5. $\boldsymbol{\beta_T}$ are coefficients for alternative-specific attributes.
6. $\boldsymbol{\beta_X}$ are coefficients for socioeconomic information of individuals.
7. $\boldsymbol{\beta_{Am}}$ are coefficients for latent attitudes.
8. $\boldsymbol{\mu_{SP}}$ is the scale factor measures the variance of SP survey in comparison to that of RP.

TABLE 5 Discrete Choice Model Results

(a) Sequential Estimation 1 – Latent Variables Model

Variable	Value (t-test)			
	Pro-walk	Pro-PT	Pro-RH	Pro-drive
Attitude Intercept ($\boldsymbol{\lambda_{0mk}}$)				
Walk safe	0 (fixed)	-	-	-
Walk comfortable	-1.56 (3.01) **	-	-	-
Walk reliable	-0.703 (1.13)	-	-	-
Walk easy	-1.29 (1.56)	-	-	-
Walk overall	-1.58 (2.26) **	-	-	-
PT safe	-	0 (fixed)	-	-
PT comfortable	-	-2.24 (2.28) **	-	-
PT reliable	-	-2.98 (2.5) **	-	-
PT easy	-	0.156 (0.219)	-	-
PT overall	-	-2.19 (2.12) **	-	-
RH safe	-	-	0 (fixed)	-
RH comfortable	-	-	-0.148 (0.371)	-
RH reliable	-	-	0.250 (0.905)	-
RH easy	-	-	-0.104 (0.249)	-
RH overall	-	-	-0.170 (0.501)	-
Drive safe	-	-	-	0 (fixed)
Drive comfortable	-	-	-	0.268 (0.429)
Drive reliable	-	-	-	0.108 (0.172)
Drive easy	-	-	-	-0.792 (0.956)
Drive overall	-	-	-	-0.505 (0.702)
Attitude parameter ($\boldsymbol{\lambda_{Amk}}$)				
Walk safe	1 (fixed)	-	-	-
Walk comfortable	1.26 (3.20) **	-	-	-
Walk reliable	1.76 (3.70) ***	-	-	-
Walk easy	2.17 (3.43) ***	-	-	-

Walk overall	2.06 (3.86) ***	-	-	-
PT safe	-	1 (fixed)	-	-
PT comfortable	-	1.69 (2.99) **	-	-
PT reliable	-	2.29 (3.33) ***	-	-
PT easy	-	0.858 (2.08) **	-	-
PT overall	-	1.93 (3.22) **	-	-
RH safe	-	-	1 (fixed)	-
RH comfortable	-	-	1.53 (4.18) ***	-
RH reliable	-	-	0.845 (3.33) ***	-
RH easy	-	-	1.52 (3.97) ***	-
RH overall	-	-	1.28 (4.11) ***	-
Drive safe	-	-	-	1 (fixed)
Drive comfortable	-	-	-	1.36 (3.27) **
Drive reliable	-	-	-	1.49 (3.55) ***
Drive easy	-	-	-	2.12 (3.83) ***
Drive overall	-	-	-	1.78 (3.71) ***
Characteristics of travelers ($\boldsymbol{\theta}$)				
Intercept (θ_{0m})	1.62 (19.5) ***	1.99 (24.1) ***	1.24 (22.7) ***	1.71 (19.8) ***
Age < 35	-0.164 (4.08) ***	-0.0827 (3.08) **	0.0757 (3.20) **	-0.214 (3.92) ***
Age > 60	-0.102 (2.43) **	0.130 (2.91) **	-0.0631 (1.60)	0.215 (3.12) **
Chinese	-0.113 (3.20) **	-0.154 (3.28) **	-0.229 (4.75) ***	-0.0366 (0.910)
Full-time job	-0.0745 (3.06) **	-0.0638 (2.51) **	0.0135 (0.640)	-0.0737 (2.07) **
Bachelor's degree and above	-0.0310 (1.71) *	0.00481(0.276)	0.0973 (3.61) ***	-0.0734 (2.44) **
Have kids under 18 years old	-0.0446 (2.02) **	-0.0558 (2.33) **	-0.0929 (3.31) ***	-0.0201 (0.686)
Male	0.0279 (1.48)	-0.0213 (1.34)	0.0359 (1.81) *	0.0713 (2.44) **
Commuter	-0.143 (4.14) ***	-0.0635 (2.91) **	-0.0875 (3.40) ***	-0.107 (3.32) ***
Threshold ($\boldsymbol{\delta}$)				
δ_{1m}	0.309 (30.4) ***	0.306 (29.3) ***	0.406 (35.4) ***	0.419 (17.6) ***
δ_{2m}	0.535 (36.3) ***	0.865 (41.3) ***	0.862 (46.3) ***	0.825 (27.0) ***
δ_{3m}	0.919 (42.0) ***	1.46 (49.0) ***	1.42 (45.8) ***	1.51 (32.4) ***
Standard deviation (σ_m^*)				
In total, 16 σ_m^* are estimated but omitted in the table.				
Statistical Summary				
Number of individuals				2,003
Number of observations				2,003
Initial log-likelihood				-74,996.85
Final log-likelihood				-50,941.04
Adjusted McFadden ρ^2				0.319

*: p-value < 0.10; **: p-value < 0.05; ***: p-value < 0.01;

(b) Sequential Estimation 2 – Discrete Choice Model

Variable	Value (t-test)	
	Base	Latent variable
Alternative Specific Constants ($\boldsymbol{\beta_0}$)		
Walk	0 (fixed)	0 (fixed)

PT	0.104 (2.24) **	0.107 (2.29) **
RH	-0.294 (5.28) ***	-0.294 (5.29) ***
Drive	0.420 (15.2) ***	0.418 (15.2) ***
AV	-0.336 (5.86) ***	0.124 (0.458)
Mode attributes ($\boldsymbol{\beta_T}$)		
Walk: Walking time (min)	-0.0354 (15.1) ***	-0.0355 (15.2) ***
PT: Travel cost ($SG)	-0.140 (11.1) ***	-0.140 (11.2) ***
PT: In-vehicle time (min)	-0.0117 (12.5) ***	-0.0118 (12.5) ***
PT: Waiting time (min)	-0.0250 (9.05) ***	-0.0254 (9.13) ***
PT: Walking time (min)	-0.0240 (12.4) ***	-0.0240 (12.4) ***
RH: Travel cost ($SG)	-0.0377 (11.7) ***	-0.0376 (11.7) ***
RH: In-vehicle time (min)	-0.0204 (9.75) ***	-0.0206 (9.82) ***
RH: Waiting time (min)	-0.0293 (7.16) ***	-0.0295 (7.19) ***
Drive: Travel cost ($SG)	-0.0724 (13.4) ***	-0.0724 (13.4) ***
Drive: In-vehicle time (min)	-0.0269 (12.4) ***	-0.0271 (12.5) ***
Drive: Walking time (min)	-0.0436 (8.09) ***	-0.0429 (7.98) ***
AV: Travel cost ($SG)	-0.0459 (12.7) ***	-0.0464 (12.7) ***
AV: In-vehicle time (min)	-0.0224 (11.1) ***	-0.0222 (11.0) ***
AV: Waiting time (min)	-0.0202 (5.80) ***	-0.0191 (5.49) ***
Individual characteristics ($\boldsymbol{\beta_X}$)		
PT: [1]Income < SG$ 4,000	0.0234 (0.738)	0.0231 (0.726)
PT: Income > SG$ 12,000	0.00392 (0.0912)	0.00423 (0.0985)
PT: Single	0.0543 (1.85) *	0.0546 (1.86) *
PT: Driver license	-0.0988 (3.22) **	-0.0994 (3.24) **
PT: Car Ownership > 1	0.177 (2.28) **	0.178 (2.30) **
RH: Income < SG$ 4,000	-0.114 (2.95) **	-0.115 (2.96) **
RH: Income > SG$ 12,000	0.135 (2.79) **	0.137 (2.82) **
RH: Single	-0.0817 (2.36) **	-0.0810 (2.34) **
RH: Driver license	-0.160 (4.35) ***	-0.160 (4.35) ***
RH: Car Ownership > 1	0.499 (5.82) ***	0.449 (5.83) ***
Drive: Income < SG$ 4,000	-0.0924 (1.75) *	-0.0927 (1.76) *
Drive: Income > SG$ 12,000	0.0981 (2.14) **	0.0979 (2.13) **
Drive: Single	-0.112 (2.94) **	-0.109 (2.86) **
Drive: Driver license	0.0986 (3.56) ***	0.0963 (3.49) ***
Drive: Car Ownership > 1	0.440 (5.45) ***	0.441 (5.46) ***
AV: Income < SG$ 4,000	-0.117 (2.88) **	-0.0851 (2.09) **
AV: Income > SG$ 12,000	0.155 (3.13) **	0.143 (2.87) **
AV: Single	-0.0657 (1.83) *	-0.148 (3.84) ***
AV: Driver license	0.0340 (0.912)	0.0323 (0.851)
AV: Car Ownership > 1	0.246 (2.82) **	0.250 (2.85) **
Latent attitudes ($\boldsymbol{\beta_{Am}}$)		
AV: Pro-walk	-	-0.146 (0.661)
AV: Pro-PT	-	-0.598 (1.98) **
AV: Pro-RH	-	0.798 (4.20) ***
AV: Pro-driver	-	-0.0548 (0.245)

Others		
SP scale (μ_{SP})	2.24 (15.0) ***	2.24 (15.0) ***
AV: [2]Std. Dev. ($\tilde{\sigma}_j$)	-	0.00 (0.00)
Statistical Summary		
Number of individuals	2,003	2,003
Number of observations	13,677	13,677
Initial log-likelihood	-20,063.67	-20,063.67
Final log-likelihood	-14,563.75	-14,533.49
Adjusted McFadden ρ^2	0.272	0.273

[1]: "Income" means household monthly income.

[2]: "Std. Dev." means standard deviation.

*: p-value < 0.10; **: p-value < 0.05; ***: p-value < 0.01;

Interpretations of the results are discussed below. It is important to not confuse people's positive attitudes towards a mode with their actual mode choice, because mode choice is also affected by price, time, and circumstantial factors.

Model Fit

1. Likelihood Test: The critical value for χ^2 distribution with 4 degrees of freedom is 9.49. Comparing the benchmark model with the latent-attitude model, the test statistic is 60.72, greater than 9.49. The inclusion of the 4 latent attitudinal variables is significant at a 95% confidence level.
2. $\boldsymbol{\mu_{SP}}$ is 2.24, meaning RP responses contain more random noise than SP responses.
3. The ASCs from the benchmark model and the new model stays almost the same for other modes except for AVs. Since ASCs represents the unknown systematic variation, the change means that some more systematic variation is captured with the inclusion of latent attitudes.

Attitudes on Existing Travel Modes on AV Adoption

We first discuss the effect of attitudes of existing modes on AV adoption.

1. Of the four existing modes, having a positive attitude towards walking and driving does not influence AV adoption. For these people, their behavior can be explained by mode-specific attributes and socioeconomic information.
2. People having a positive attitude towards ridesharing are more likely to choose AV as well. Likely there could be a competition between on-demand AVs and on-demand ridesharing. At the same time, there are opportunities for ridesharing companies to adopt the AV model.
3. People having a positive attitude towards public transit are less likely to choose AV. For people who take transit if transit is their preferred mode of travel, this suggests that they do not easily switch to AVs unless there is significant incentives in generalized travel cost compared to the current setting. For people who take transit if they have to, AVs probably will not take over this part of the market either.

Latent Attitudes Measurement

From the loadings of attitude coefficients onto different indicators, we are able to identify the indicator question that mostly reflects people's overall attitude.

1. For all modes, although the attitude is loaded onto the 'overall' indicator quite heavily, the 'overall' indicator does not get the highest loading. For walking and driving, the attitudes have

the greatest influence on 'easy'; for public transit, it is 'reliable'; and for ridesharing, it is 'comfort'. These indicators are influenced by people's attitudes towards that mode the most.

Characteristics of Travelers

Characteristics of travelers are divided up into two groups. The first group of variables fits people's attitudes towards existing modes, which then indirectly affect the mode choice. The second one fits people's actual choices in the survey, which may directly influence the mode choice.

1. The group that directly influence mode choice is: income, driver's license, car ownership, and marital status; and the one that indirectly influence mode choice is: age, ethnicity, employment, education level, having kids, and gender. Characteristics from the first group is more directly related to trip-making; while the second group characterizes the individual, hence his/her attitude.
2. Using walking as a benchmark, having ***higher income*** increases the likelihood of using driving, rideshare, and AV, while having ***lower income*** decreases the likelihood. It shows that AV may probably be adopted by the privileged at first.
3. ***Younger*** people have more positive attitudes towards ridesharing and ***elder*** people have more positive attitudes towards driving and public transit. It hints that young generations are keener on new mobility modes and technology.
4. People with a ***full-time job*** and ***higher education*** have more positive attitudes towards ride sharing. This could also speak for which group of people are more open to new mobility modes and technology. This group of people probably have more opportunities to interact with technology and are more capable of accepting and learning new things.
5. ***People with kids*** and ***commuters*** generally have more negative attitudes towards all modes. These people probably have endured the inconvenience of travelling the most therefore possess more negative attitudes in general.
6. ***Gender*** does not seem to be significantly correlated with people's attitudes.
7. ***Having a driver's license*** and ***owning cars*** have a positive correlation with driving.

Mode-Specific Attributes

First of all, all time and cost related variables have negative coefficients. For all modes, in-vehicle travel time gives less disutility than walking and waiting time.

1. Values of in-vehicle time for the PT, RH, driving, AV are \$5.1, \$32.9, \$22.5, and \$28.7 per hour, respectively. Comparing the cost and in-vehicle time coefficients across modes, people are the most sensitive to PT travel cost and least sensitive to PT travel time, meaning that people take public transport with the expectation that it is not time-efficient. People are expecting AVs to be time-efficient, consistent with our findings that AVs are probably for the wealthier population at its introduction.
2. Effect of waiting times are similar across modes, while walking time provides a large disutility to driving. When people choose driving, they want to walk less.

CONCLUSION AND DISCUSSION

This paper focuses on how latent attitudes towards existing travel modes affect individual choices on AV adoption based on a dynamic SP survey. The respondents are asked to rate on a 7-point Likert scale of their impressions on existing travel modes according to the following dimensions: safety, easiness, comfort, and overall impression. A confirmatory factor analysis is performed to get the latent attitudes of each individual on each existing mode and the attitudes are then factored into a latent-variable discrete choice model.

The results suggest that latent attitudes towards existing modes are influential towards the adoption of AVs. The model fits better with the inclusion of latent attitudes, and the likelihood test suggests that the four attitudinal variables are significant at 95% confidence. In particular, people with goodwill towards public transit tend not to choose AVs and people who currently have a good impression on ridesharing services are more positive towards AVs. Therefore, in further studies of AV demand and the design of AV pilot services, we suggest to carefully explore the modal shift and the supply-side competition between on-demand AVs and chauffeured ridesharing services.

The value of time for people choosing AVs is comparable to those of driving and ride hailing, which is much higher than public transit. Our results show that, the highly educated, wealthy, and/or younger people tend to be more friendly towards new technologies. Such groups of people have more positive attitude toward ridesharing, which is also relatively new, and highly correlated with AV adoption. These suggest that AVs, like any new technology, at least in the short term, probably will not be directly competing with public transit, nor will it be a solution to transportation equity. These findings on the audience of AVs which help inform and shape how AVs can be integrated into the existing network while developing AV technology, marketing plan, and service planning.

This study calls for further studies on the relationship between AV and existing modes. Besides latent variables, another possibility is to assign individuals to latent classes and investigate how close their attitudinal classes are related to their actual choices using a revealed preference survey. Additionally, since the current survey is based on the premise that AV is an on-demand service, to follow up on the possible competition between AV and chauffeured ridesharing, and on the possible cooperation between AV and public transit, more direct research could be done on the design characteristics of autonomous public transit, as well as people's possible reactions to this concept.

AUTHOR CONTRIBUTION STATEMENT

The authors confirm contribution to the paper as follows: study conception and design: B. Mo, Y. Shen, J. Zhao; data collection: B. Mo, Q.Y. Wang, Y. Shen, J. Zhao; analysis and interpretation of results: Q.Y. Wang, B. Mo, Y. Shen; draft manuscript preparation: B. Mo, Q.Y. Wang, Y. Shen. All authors reviewed the results and approved the final version of the manuscript.

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