Transportation Research Part C 130 (2021) 103281

Contents lists available at ScienceDirect

Transportation Research Part C

journal homepage: www.elsevier.com/locate/trc

Impacts of subjective evaluations and inertia from existing travel modes on adoption of autonomous mobility-on-demand

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ARTICLE INFO

Keywords:
Autonomous vehicles
Mode choice
Mixed logit model
Factor analysis
Latent variables
Inertia

ABSTRACT

As autonomous vehicle (AV) technology advances, it is important to understand its potential demand and user characteristics. Literature from stated preference surveys find that attitudes and current travel behavior are as or more important than demographics in determining intention to purchase or use AVs. Yet to date no study has looked at how attitudes and use of existing modes both simultaneously affect AV adoption. In this study, we conduct a stated preference survey in Singapore to investigate how the subjective evaluation of existing travel modes (attitudes) and inertia based on previous use of existing modes affect the adoption of an autonomous mobility-on-demand service (AMOD). Using a sample size of 2,003 individuals and 11,613 choice observations, we estimate a mixed logit discrete choice model incorporating latent variables capturing subjective evaluations of existing travel modes (determined through confirmatory factor analysis), a two-part formulation of modal inertia, and other trip-specific and socio-demographic variables. Results show that subjective evaluation and use of existing modes both affect the adoption of AMOD. Specifically, people with a positive evaluation of ridehailing and those who are current ridehailing users are more likely to choose AMOD. Additionally, those who are current car drivers are more likely to choose AMOD, while users of public transit were less likely to choose AMOD. Given that ridehailing is the closest existing mode to our hypothetical AMOD service, our results might suggest that how AVs are implemented and their similarity to existing modes may be critical to the formation of attitudes and direction of inertia impacting adoption. Our research provides insights on the potential relationship between AVs and existing modes that could valuable in AV network design and service planning.

1. Introduction

As autonomous vehicle (AV) technology continues to advance, it is important to understand how it will impact our existing

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https://doi.org/10.1016/j.trc.2021.103281
Received 15 March 2020; Received in revised form 16 April 2021; Accepted 25 June 2021
Available online 14 July 2021

transportation systems. However, many factors make these future impacts uncertain, including how the technology will be deployed and regulated, whether infrastructure will change along with the vehicles, how service models and markets will adapt, and how individual consumers will adopt the technology, potentially changing their existing travel behavior (Fagnant and Kockelman, 2015). Given that AVs have not yet moved beyond development and testing to full commercial deployment, analyzing the long-term effects of AVs on transportation systems and travel behavior rely on modeling of potential future scenarios (e.g., Basu et al., 2018; Nieuwenhuijsen et al., 2018; Milakis et al., 2017; Gruel and Stanford, 2016).

One of the most pivotal aspects to consider in constructing these future scenarios is the adoption behavior of individual travelers. Because adoption of emerging technologies is uncertain and heterogeneous, consumers' perceptions of and intentions to use AVs have been an active area of research in recent years. Since AVs are not yet commercially available, most studies make use of hypothetical stated choice surveys to analyze people's willingness to pay for and likelihood to adopt AVs (e.g., Gkartzonikas and Gkritza, 2019; Becker and Axhausen, 2017). Past studies have found separately that attitudes towards AVs and existing travel behavior play a significant role in predicting AV adoption (in addition to individual socio-demographics). However, no study to date has looked at how people's perceptions and use of current travel modes both simultaneously influence and help forecast AV adoption.

To address this research gap, this study analyzes the impact of people's perceptions and use of current travel modes on the adoption behavior of AVs with a stated preference survey. In particular, the study aims to answer the following questions:

- How does the subjective evaluations of existing travel modes influence AV adoption and potential substitution patterns between different modes?
- How does use of existing travel modes (modal inertia) affect AV adoption?
- Are the impacts of subjective evaluations and use of existing travel modes distinct? And, if so, are they consistent?

In answering these research questions, this study contributes to both our substantive understanding of AV adoption as well as methodological state-of-practice regarding survey designs and econometric models to analyze the problem.

The study is conducted in Singapore, which is a world leader in adopting new transport technologies and experimenting with different policy regulations and aims to be one of the first markets to adopt AVs if they become commercially available (Abdullah, 2019). Specifically, we consider the adoption of an autonomous mobility-on-demand (AMOD) service in which a fleet of AVs are dynamically matched with trip requests. This is the form of AV deployment that the Singapore Land and Transport Authority (LDA) has announced to pilot and deploy (Bhunia, 2017).

The rest of this paper is organized as follows. Section 2 reviews existing literature on AV adoption analysis; Section 3 discusses the survey design; Section 4 provides details on model formulation; and Section 5 presents the model results. We conclude with a discussion of the results, study limitations, and potential for future studies in Section 6.

2. Literature review

A growing body of literature is exploring the questions of who will adopt AVs, when, and in what form. Gkartzonikas and Gkritza (2019) recently provided a comprehensive review of the literature characterizing potential AV user preferences and behaviors. Most of the studies reviewed use descriptive statistical analyses and regression methods of stated preference survey data to identify socio-economic, travel characteristics, and attitudes of individuals affecting AV adoption choices and willingness to pay under different implementation scenarios (e.g., privately-owned vs. fleet-based, as first/last mile service for public transit, etc.).

Existing research has found that, similar to traditional mode choice, trip characteristics like travel time and travel cost as well as attributes of the built environment are critical predictors of AV adoption (Gkartzonikas and Gkritza, 2019; Nodjomian and Kockelman, 2019; Shabanpour et al., 2018; Becker and Axhausen, 2017; Bansal et al., 2016; Krueger et al., 2016; Yap et al., 2016). Other studies show that socio-demographic characteristics of the traveler also help determine AV adoption decisions. For example, multiple studies have found that younger and more wealthy people have higher interests in and willingness to adopt AVs (Spurlock et al., 2019; Shabanpour et al., 2018; Bansal et al., 2016; Krueger et al., 2016). While the role that gender plays is less certain (Cai et al., 2019; Spurlock et al., 2019; Bansal et al., 2016). Another group of studies have demonstrated that an individual's previous travel experiences, particularly of car crashes, are correlated with greater interest in AVs and their potential safety benefits (Shabanpour et al., 2018; Bansal et al., 2016).

2.1. General attitudes and perceptions of autonomous vehicles

Some studies have explored the critical influence of attitudinal factors on people's stated intention to adopt AVs. One subset of this literature explores how general attitudes towards risk (Wang and Zhao, 2019), innovation and interest in new technologies (Lavieri and Bhat, 2019; Haboucha, et al., 2017), and environmental concerns (Haboucha, et al., 2017; Yap, et al., 2016) affect intention to adopt AVs. Others have considered the influence of perceptions of AV technology, including benefits and performance (Liu, et al., 2019; Hewitt, et al., 2019; Madigan, et al., 2016; Payre et al., 2014; Fraedrich and Lenz 2014; Schoettle and Sivak 2014), safety and trust (Liu, et al., 2019; Yap, et al., 2016; Bansal et al., 2016; Kyriakidis et al., 2015; Payre et al., 2014; Fraedrich and Lenz 2014; Howard and Dai, 2013), and hedonic enjoyment (Payre et al., 2014).

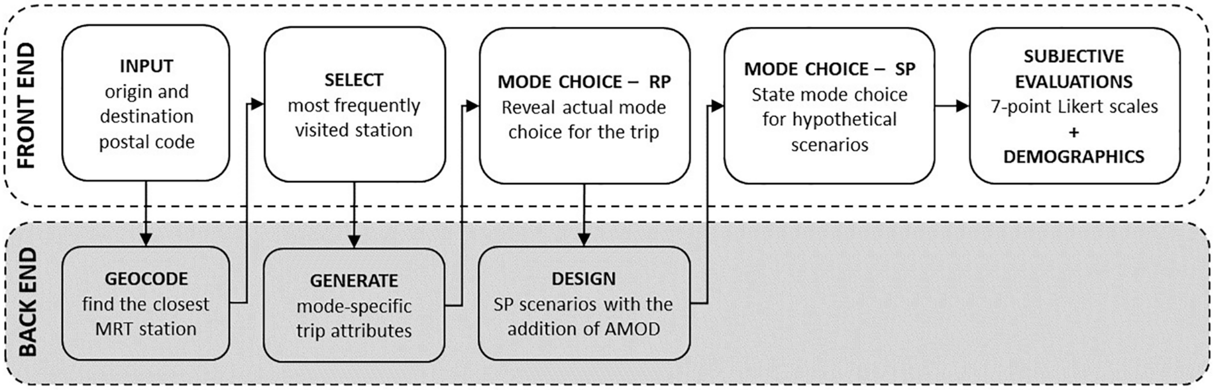

Fig. 1. Survey process diagram.

2.2. Existing travel behavior

A more limited number of studies have linked existing travel behavior—by private car, transit, biking, and walking—to their adoption of AMOD. Krueger et al. (2016) found that those who travel exclusively by private car or taxi are more likely to adopt AMOD, and Haboucha et al. (2017) observed that those without transit experience are less likely to use AMOD. A recent study conducted in Singapore separately estimating choice models for drivers and transit users and found that their tendencies to switch to AMOD are different (Cai et al., 2019).

3. Our contribution

While the above studies have explored many of the factors that traditionally influence mode choice, few of them explicitly account for the fact that AMOD would be introduced into an urban mobility system in which there are incumbent modes and established travel patterns. In such situations, both attitudes and actual use of existing transportation modes may influence consumer adoption of AV technology. While previous studies have considered the impact of attitudes towards AV technology on adoption, none have incorporated attitudes towards or perceptions of incumbent travel modes. Furthermore, while some studies have considered how adoption differs among users of cars, transit, and other modes or the influence of travel habits, these studies have not explicitly modeled how the inertia of existing travel behavior might influence AV choice.

In this study, we add to existing literature by considering how both subjective evaluations and actual use of existing travel modes impact adoption of AMOD over other modes of travel. Research in psychology has firmly established that people's attitudes and actual behaviors are distinct (e.g., Ajzen and Fishbein, 1977) and can even be at odds if choices are constrained (e.g., de Vos, 2018 for a transportation application and Festinger, 1962 for a general theory of cognitive dissonance). Therefore, we hypothesize that subjective evaluations (attitudes) and inertia are distinct factors that both influence whether an individual will switch from their current travel behavior and adopt a new AMOD service. We incorporate these two concepts into a state-of-the-art hybrid choice model that includes trip characteristics and traveler characteristics and allows for heterogeneity in estimated sensitivities to these explanatory variables (McFadden and Train, 2000). We use confirmatory factor analysis to estimate latent variables representing subjective evaluations of existing travel modes and add them to the model. We incorporate existing use of travel modes as measures of inertia (Cherchi et al., 2017; Cherchi and Manca, 2011; Train, 2009; Yáñez, 2009; Cantillo, et al., 2007). This approach enables us to study the potential substitution patterns of AMOD with other travel modes which can help identify potential user groups of AMOD and draw insights on AV system design.

4. Survey design and data

This study incorporates people's subjective evaluations and inertia into the analysis of potential adoption of AMOD services, using data collected from a dynamic online survey administered in Singapore in July 2017 (Shen et al., 2019). Here we present the details on the survey design, introduce the key variables used in the study, and discuss the representativeness of our sample of 2,003 individuals and 11,613 choice observations.

4.1. Survey design

The survey consisted of four parts: a revealed preference (RP) travel diary of a typical trip for a given purpose, a series of stated preference (SP) choice experiments with AMOD as a new potential travel mode for the trips in the respondents' travel diaries, and questions about respondents' perceptions of existing modes and socio-demographic information. Fig. 1 shows the survey procedure.

In the RP portion of the survey, each respondent was first presented with a trip purpose—commute (to work or school), shopping

Table 1
SP attribute generation by mode.

Mode	Static Attributes		Trip-Specific Attributes	
	Name	Levels	Name	Levels
Walk			Walk time	RP response ×
Public transit (PT)	Cost ($S)	0.5, 0.9, or 1.5	Walk time	0.5, 1, or 1.5
	Wait time (min)	3, 5, or 10	In-vehicle time	
Ridehailing (RH)	Wait time (min)	1, 3, or 8	Cost	
			In-vehicle time	
Autonomous mobility-on-demand (AMOD)	Wait time (min)	1, 3, or 8	Cost	
			In-vehicle time	

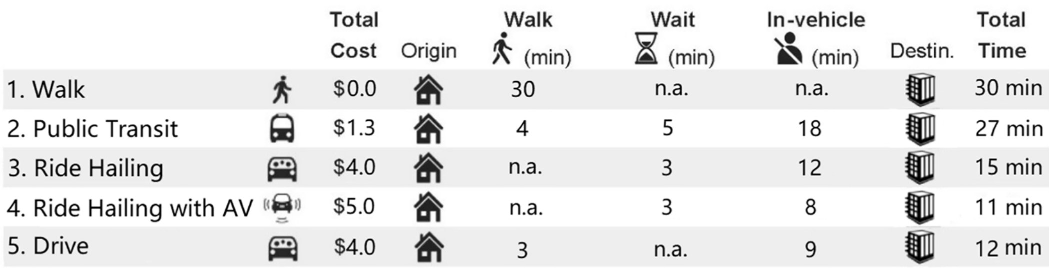

Fig. 2. Example interface for stated preference choice experiment.

Table 2
Indicators used to derive latent variable measures of subjective evaluation of existing travel modes.

Subjective evaluation (latent variable)	Indicator	Question
Pro-walk	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 enjoyable	I enjoy walking.
Pro-public transit (PT)	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 enjoyable	I enjoy taking public transport.
Pro-ridehailing (RH)	RH safe	I think ridehailing feels safe.
	RH comfortable	I think ridehailing is comfortable.
	RH reliable	I think ridehailing is a reliable mode.
	RH easy	I think ridehailing is easy.
	RH enjoyable	I enjoy ridehailing.
Pro-drive	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 enjoyable	I enjoy driving.

(to grocery store or supermarket), or recreation/entertainment. The respondents were then asked to report the postal codes of trip origin (O) and destination (D), and the mode with which the trip was usually made. Based on the respondent's revealed OD, some attributes, including walking time, bus access walking time, bus in-vehicle time, ridehailing in-vehicle time, and ridehailing travel cost, were trip-specific and obtained from Google API. Other attributes, including bus travel cost, bus waiting time, and ridehailing waiting time, were static and taken to be the market average.

For the SP portion of the survey, the respondents were asked to choose among incumbent modes (bus, walk, drive, and ridehailing) and a new AMOD service (ridehailing with AV) for the same trip purpose as RP but with varying levels of trip attributes. AMOD was chosen for the study since this was the main form of AV deployment being piloted in Singapore at the time of data collection (Bhunia, 2017). To make sure all respondents were aware of the new technology being presented, every respondent watched an introductory video before answering the SP questions.

Similar to the RP portion, there were static and trip-specific attributes in the SP choice experiment. The static attributes had three levels, with the median anchored to the market average and the high/low values set to the levels specified in Table 1. Each trip-specific attribute also had three levels, with the median anchored to the value calculated from the RP responses, to make the choices were more

Table 3
Socio-demographic characteristics of survey sample compared to Singapore population.

Socio-demographic characteristics	Bin	Sample (%)	Population (%)
Age (as percent of adult population aged 20 or older, 2017)	20–29	29.1	17.5
	30–39	24.6	18.5
	40–49	23.4	19.6
	50–59	15.5	19.6
	60 and older	7.4	24.8
Gender (2017)	Male	45.8	49.0
	Female	54.1	51.0
Ethnicity (2017)	Chinese	85.0	74.3
	Malay	6.0	13.4
	Indian	4.5	9.0
	Other (or declined to answer)	4.5	3.2
Monthly household income (S$) (2017)	Not working or below 2,000	10.2	19.0
	2,000 – 3,999	15.2	10.6
	4,000 – 5,999	15.9	10.6
	6,000 – 7,999	15.9	10.4
	8,000 – 9,999	13.7	9.6
	10,000 – 11,999	10.8	7.9
	12,000 – 14,999	4.7	8.9
	15,000 – 19,999	8.6	9.7
	20,000 and over	5.0	13.3
Educational attainment (2016)	Below secondary	0.3	29.3
	Secondary	10.1	17.9
	Post-secondary (non-tertiary)	6.1	8.9
	Diploma or professional qualification	26.1	14.7
	University	57.4	29.1
Marital status (2016)	Single, never married	44.3	31.6
	Married or domestic partnership	51.5	29.5
	Widowed	0.8	5.3
	Divorced or separated	3.3	3.6
Household car ownership (2017)	0	43.5	64.7
	1 or more	56.5	35.3

Table note: Population data comes from the Singapore Department of Statistics: age for adult population 20 years and older, gender, ethnicity, marital status, and educational attainment for population 25 and older (Singapore Department of Statistics., 2018); household income (Singapore Department of Statistics., 2020); and car ownership for 2017/2018 (Singapore Department of Statistics, 2021).

realistic and familiar to the respondents. High/low values were set as 1.5 and 0.5 times the value given in the RP responses, respectively. For the AMOD service (not present in RP), trip-specific attributes were assumed to be similar to those of ridehailing and prices were determined according to the pricing schemes of Uber/Grab at the time in Singapore (Shen et al., 2019; Mo et al., 2021). Given these attributes level, a partial orthogonal balanced design was generated, resulting in 27 scenarios. Six out of these 27 SP scenarios were randomly chosen for each respondent to answer sequentially. While this random blocking destroys the perfect orthogonality of the research design, it is a typical question generation procedure used in AV choice experiments to limit the number of complex questions answered per respondent (e.g., Haboucha, Ishaq, and Shiftan, 2017; Krueger, Rashidi, and Rose, 2016). A sample interface seen by respondents is shown in Fig. 2.

The third part of the survey included Likert-scale questions on the subjective evaluation of existing travel modes. Based on studies by Kroesen et al. (2017) and Molin et al. (2016), we selected five key attributes of the current travel modes to make up the subjective evaluation: reliability, ease to use, safety, comfort, and enjoyment. The specific statements are shown in Table 2. For each statement, responses were collected on a 7-point Likert scale, ranging from “totally disagree” (1) to “totally agree” (7).

4.2. Sample Socio-demographics and representativeness

The final portion of the survey collected the socio-demographic information for each respondent, including gender, ethnicity, employment, age, education, income, and car ownership. To determine the representativeness of our sample, we compared the share of individuals by gender, age, ethnicity, educational attainment, income, and car ownership in our sample to available population statistics. We find that our sample overrepresented males, younger and more highly educated individual, and middle-income, car-owning households (see Table 3).

Because there are clear differences between the sample and the population in certain demographic categories, we calculate survey weights using iterative proportional fitting (IPF or raking). Weights were calculated using the *anesrake* package in R (Pasek, 2018), which implements the American National Election Study (ANES) weighting algorithm documented in (DeBell and Krosnick, 2009). Convergence was reached so that weighted sample proportions exactly match the population proportions for all characteristics listed in Table 3.

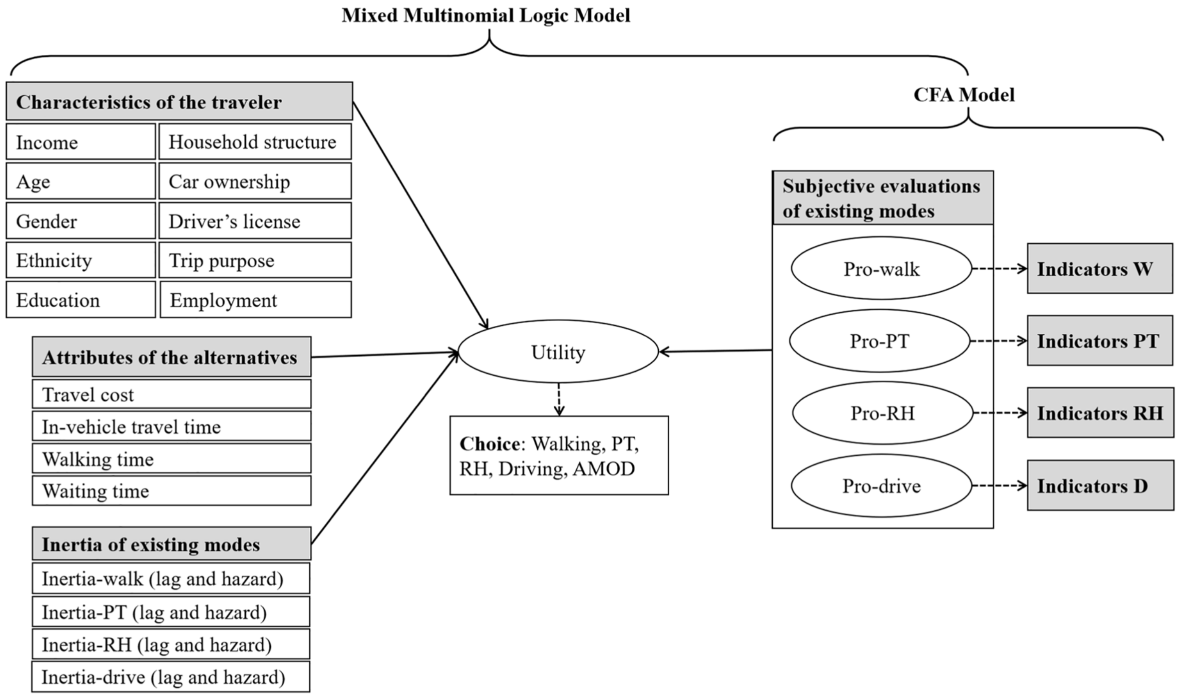

Fig. 3. Path diagram of the hybrid choice model. *Figure note:* Rectangual boxes represent observed variables such as characteristics of respondents and attributes of choice alternatives (modes), inertia variables, psychometric indicators, and mode choices are represented by rectangular boxes; ovals represent latent variables such as utilities and subjective evaluations; solid arrows represent structural equations; dashed arrows represent measurement equations. The CFA model and MMNL model were estimated sequentially, with factor scores for each subjective evaluation latent variable treated as observed variables in the choice model.

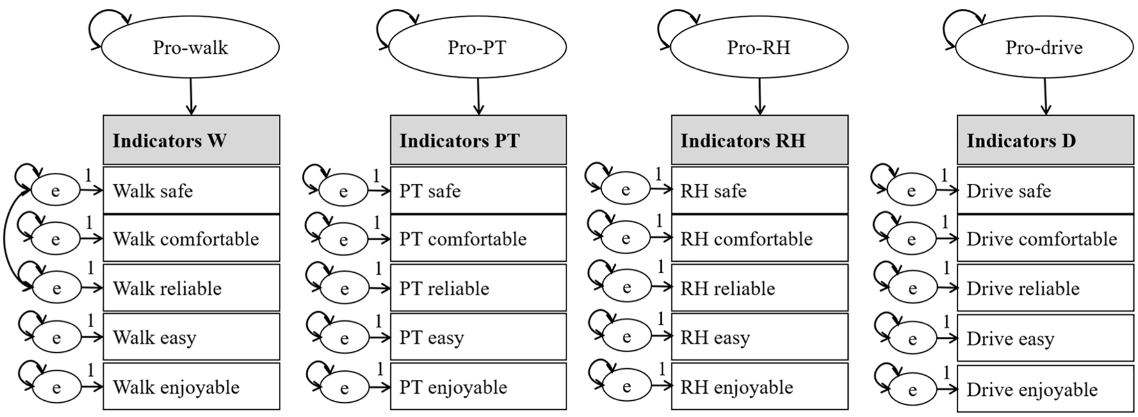

Fig. 4. Structure of the Confirmatory Factor Analysis models for the subjective evaluation of existing travel modes.

5. Model specification

In this study, a hybrid choice model was used to measure the impact of people's subjective evaluations and inertia on the potential adoption of AMOD. The high-level model structure is shown in Fig. 3. First, the respondent's subjective evaluations of the existing modes were captured by four latent variables estimated from confirmatory factor analysis (CFA). Additionally, the concept of inertia was built from the use of previous travel modes (RP responses) and choices made in previous choice situations in SP responses. Then, these estimated factor scores and inertia measures were entered into a mixed multinomial logit (MMNL) model, along with the demographic and trip-specific attributes presented in the survey. The model was estimated using a sequential estimation approach. The following sections describe each step of the process in detail.

5.1. Subjective evaluations

Respondent's subjective evaluations of existing travel modes—walking, public transit (PT), ridehailing (RH), and driving—are estimated as latent variables based on responses to five indicators related to safety, comfort, reliability, ease of use, and enjoyment of use (see Table 2). Responses for each indicator were recorded on a 7-point Likert scale, which we treat as ordinal following best-practice recommendations when including latent factors in hybrid choice models (Bahamonde-Birke and de Dios Ortúzar, 2017). CFA is used to develop and validate each latent variable as discussed further in Appendix A.

The CFA model structures are shown in Fig. 4, with each latent variable validated and estimated separately. The latent variables represent the subjective evaluations of existing modes, and are indexed by $m = \{1,2,3,4\}$that represents pro-walk, pro-PT, pro-RH and pro-drive, respectively. The indicators were assumed to be independent except for the indicators of safety and reliability for the pro-walk latent variable based on Lagrange modification indices in the CFA model (see Appendix A).

Denote the m-th latent variable of individual n as A_{nm}. Let Z_{nmk} be the response to individual n's response the k-th indicator statement corresponding to the m-th latent variable, where $k \in Q_m$ and Q_m is the set of indicators for m-th latent variable found in Table 2. For example, for $m = 1$ (pro-walk), $Q_m = \{$Walk safe, Walk comfortable, Walk reliable, Walk easy, Walk enjoyable$\}$.

Z_{nmk} takes values on a 7-point Likert scale, and is therefore an ordinal variable. However, the typical CFA model requires the dependent variable to be continuous. A conventional way to model ordinal responses in CFA is assuming that there is an underlying unobserved continuous variable $Z^*_{nmk} \in (-\infty, +\infty)$ that drives the ordered responses Z_{nmk} (Yang-Wallentin et al., 2010; Muthén, 1984). The measurement equation of Z^*_{nmk} is assumed to have the following form:

$$Z^*_{nmk} = \theta_{0mk} + \theta_{1mk}A_{nm} + \eta_{mk} (1)$$

where θ_{0mk} is the intercept; θ_{1mk} is the factor loading of the m-th latent variable onto indicator k; and$\eta_{mk} \sim \mathcal{N}(0, \sigma_{mk})$ is a normally distributed error term for the m-th latent variable. Note that η_{mk} ($\forall k \in Q_m$) are assumed to be independent unless correlations are introduced explicitly into the model.

The relationship of Z_{nmk} and Z^*_{nmk} can be expressed as

$$Z_{nmk} = c \Leftrightarrow \tau_{m,c-1} < Z^*_{nmk} < \tau_{m,c} (2)$$

where $c \in \{1, 2, \cdots 7\}$ is the 7-point Likert scale. $\tau_{m,c}$ is the threshold parameter for answer c and it follows that $-\infty = \tau_{m,0} < \tau_{m,1} < \cdots < \tau_{m,7} = +\infty$. Therefore, the probability of observing Z_{nmk} given the latent variable A_{nm} can be expressed as:

$$\Pr(Z_{nmk}= c|A_{nm}) = \Pr\left(\tau_{m,c-1} < Z^*_{nmk} < \tau_{m,c}|A_{nm}\right) = \int_{\tau_{m,c-1}-\theta_{0mk}-\theta_{1mk}A_{nm}}^{\tau_{m,c}-\theta_{0mk}-\theta_{1mk}A_{nm}} \phi_{mk}(\eta)d\eta (3)$$

where $\phi_{mk}(\cdot)$ is the probability density function of η_{mk}.

To obtain the factor scores for each latent variable for each individual ($\widehat{A}_{nm}$), the expected a posteriori (EAP) method is used (Estabrook and Neale, 2013; Shi and Lee, 1997). Specifically,

$$\widehat{A}_{nm} = E[A_{nm}] = \int_w w f_{A_{nm}|\mathbf{Z}}(w)dw = \int_w w \frac{f_{A_{nm}}(w)\Pr(\mathbf{Z}|A_{nm}= w)}{\int_{w'} f_{A_{nm}}(w')\Pr(\mathbf{Z}|A_{nm} = w')dw'} dw$$

where $E[\bullet]$ is the expectation. $f_{A_{nm}|\mathbf{Z}}(\bullet)$ is the posteriori probability density function of A_{nm}. $\mathbf{Z}$ is the vector of all Z_{nmk}.$\Pr(\mathbf{Z}|A_{nm}= w)$ can be calculated as the product of all $\Pr(Z_{nmk}|A_{nm} = w)$. $f_{A_{nm}}(\bullet)$ is the prior probability density function of A_{nm}. Eq. 4 indicates that $A_{nm} = \widehat{A}_{nm} + \delta_m$, where δ_m is an error term with mean of zero. In this study, we assume $\delta_m \sim \mathcal{N}\left(0, \sigma^2_m\right)$ for the convenience of the MMNL model estimation.

5.2. Inertia of existing travel modes

An individual's previous experience may impact their current choice (often termed "inertia"). When individuals are faced with new situations, inertia represents the tendency to stick with past choices rather than the disposition to change (Train, 2009; Yáñez, 2009; Cantillo et al., 2007). In this study, we hypothesize that the current use of travel modes poses an inertial effect in the respondents' stated preferences. The definition of inertia was adapted from Cherchi et al. (2017) in which inertia was formulated considering both lagged and hazard effects[1], accounting for inertia from the previous use of existing modes and from repeated selection of an existing mode in the survey.

The sequence of each question is labeled as choice situation t, where $t = 0$ for the RP question and $t = \{1, \cdots, 6\}$ for the SP questions. The lagged inertia of mode j for individual n in choice situation t, denoted asI^{L}_{njt}, represents the lagged effect of individual n's previous choice in the RP question on the individual's current choice. Therefore, I^{L}_{njt} takes the value 1 if the current choice agrees with the previous choice and 0 otherwise. Mathematically,

$$I^{\mathrm{L}}_{njt} = \begin{cases} 1, if Y^{RP}_n = j \\ 0, otherwise \end{cases} \forall j \in S, t \geq 1 (5)$$

where Y^{RP}_n is the choice of individual n in the RP portion, and $S = \{$Walk, PT, RH, Drive$\}$ is the set of existing travel modes.

[1] A "habit" latent variable is considered in Cherchi et al., (2017) in the inertia formulation. But it is not available in our study. We therefore drop the components that include latent variables.

The second type of the inertia accounts for the effect that as more inertia is formed if the mode is selected more often in the panel data, and therefore is a function of the number of times that a mode is selected in different choice situations by the same individual. Let I^{H}_{njt} represent the hazard inertia of mode $j$for individual n in choice situation t, and it is assumed to have the inverse Weibull distribution:

$$I^{\mathrm{H}}_{njt} = \left(FRE_{njt}\right)^{1-\gamma_j} \forall j \in S, t \geq 1 \quad (6)$$

where FRE_{njt} is the adjusted number of times mode j is selected from choice situations 0 (RP) to $t-1$ for individual n. The adjustment is done on FRE_{njt} by increasing it one unit as the respondent selects mode j and decreasing it one unit as the respondent switches to another mode (Cherchi et al., 2017). Note that FRE_{njt} will not be further decreased when it reaches 0. $\gamma_j \in [0, 1]$ is the hazard function parameter (HFP) to be estimated.

These two types of inertia are both included in the utility specification for each mode, capturing inertia effects from the previous use of existing modes and repeated selection of an existing mode in the survey.

5.3. Mixed multinomial logit model

To model people's choices, a MMNL was formulated, with the overall model structure shown in Fig. 3. Utilities of the alternative modes consist of alternative-specific trip attributes, individual characteristics, subjective evaluations of existing travel modes (latent variable factor scores from CFA) and use of existing modes (inertia). Since RP and SP questions capture people's observed past choices and expected future choices, respectively, their utility functions should be modeled separately (Ben-Akiva et al., 1994). Individual n's utility of mode j in choice situation $t$is defined by:

$$U^{RP}_{nj} = V^{RP}_{nj} + \varepsilon^{RP}_{j} = \beta^{ASC}_{j} + \boldsymbol{\beta}^{T}_{j}\boldsymbol{T}^{RP}_{nj} + \boldsymbol{\beta}^{X}_{j}\boldsymbol{X}_{n} + \sum_{m=1}^{4}\beta^{A}_{mj}\left(\widehat{A}_{nm} + \delta_m\right) + \varepsilon^{RP}_{j} \quad \mathbf{(7)}$$

$$U^{SP}_{njt} = V^{SP}_{njt} + \varepsilon^{SP}_{j} = \beta^{ASC}_{j} + \boldsymbol{\beta}^{T}_{j}\boldsymbol{T}_{njt} + \boldsymbol{\beta}^{X}_{j}\boldsymbol{X}_{n} + \sum_{m=1}^{4}\beta^{A}_{mj}\left(\widehat{A}_{nm} + \delta_m\right) + \sum_{j^{'} \in S}\beta^{L}_{j^{'}j}I^{L}_{nj^{'}t} + \sum_{j^{'} \in S}\beta^{H}_{j^{'}j}I^{H}_{nj^{'}t} + \varepsilon^{SP}_{jt} \quad \mathbf{(8)}$$

where U^{SP}_{njt} and U^{RP}_{nj} are the utility functions of the SP and RP, respectively. The subscript t in RP utility function is ignored because there is only one RP choice situation and $t = 0$ for RP by definition. β^{ASC}_{j} are the alternative-specific constants; $\boldsymbol{T}^{RP}_{nj}$ and $\boldsymbol{T}_{njt}$ are alternative-specific trip attributes of mode j;$\boldsymbol{X}_n$ is the vector of socio-demographic variables of individual n; $\boldsymbol{\beta}^{X}_{j}$, $\boldsymbol{\beta}^{T}_{j}$, β^{A}_{mj}, $\beta^{L}_{j^{'}j}$, and $\beta^{H}_{j^{'}j}$ are the coefficients to be estimated; ε^{RP}_{j} and ε^{SP}_{jt} are the Gumbel-distributed error term for the RP and SP questions, respectively. The scale of RP data (μ_{RP}) is normalized to 1 and the scale of SP data is denoted as μ_{SP}, which will be estimated in the model.

Let $\delta_j = \sum_{m=1}^{4}\beta^{A}_{mj}\delta_m$ represent the aggregated normal error term with distribution $\mathcal{N}(0, {\sigma_j}^2 = \sum_{m=1}^{4}\left(\beta^{A}_{mj}\sigma_m\right)^2)$. Note that δ_j are independent from each other based on our CFA model structure. Thus, the probability for an individual n choosing mode j can be expressed by the following equation:

$$\Pr(Y_{nt} = j) = \int \Pr\left(Y_{nt} = j | \delta_j = w\right)\phi_{\delta_j}(w)dw = \int \frac{\exp(\mu V_{njt})}{\sum_{j^{''} \in C_n}\exp(\mu V_{nj^{''}t})}\phi_{\delta_j}(w)dw \quad (9)$$

where Y_{nt} is the mode choice of individual n at situation t; $\phi_{\delta_j}(w)$ is the probability density function of δ_j; C_n is the choice set for individual n; Note that for RP questions, we have $\mu = \mu_{RP} = 1$ and $V_{njt} = V^{RP}_{nj}$ according to Eq. 7; while $\mu = \mu_{SP}$ and $V_{njt} = V^{SP}_{njt}$ for SP questions according to Eq. 8.

Since our research question is the extent to which subjective evaluations and use of existing modes impact the adoption of a new AMOD service, we include evaluations and inertia for all existing modes in the utility function for AMOD. The utility functions of existing modes (walking, PT, RH, and driving) only contain the subjective evaluation and inertia of that specific mode. Because people often walk as part of PT trips, we also add subjective evaluation and inertia of walking into the utility of PT. Further, we assume that all modes are available to all individuals except for driving, and driving is available to individuals with a driver's license.

5.4. Model estimation

The overall likelihood function of the hybrid model can be written as a combination of the CFA model and the MMNL model:

$$L(\boldsymbol{\theta}, \boldsymbol{\beta}, \boldsymbol{\sigma}, \mu_{SP}) = \prod_{n=1}^{N}\prod_{t=0}^{T}\Pr(Y_{nt})\hat{\text{A}}\cdot\prod_{m=1}^{4}\prod_{k\in Q_m}\Pr(Z_{nmk}) \quad (10)$$

where $\boldsymbol{\theta}, \boldsymbol{\beta}, \boldsymbol{\sigma}$ and μ_{SP} are the coefficients to be estimated. $T = 6$ is the number of SP questions. There is no closed form expression for $\Pr(Y_{nt})$ as it includes an integral of Gaussian distribution. Thus, maximum simulated likelihood (MSL) is used (Train, 2009). Although simultaneous estimation of both the MMNL and the CFA models is theoretically possible and statistically efficient since it includes full information on measurement error into the estimation of all model parameters, this approach is computationally inhibitive. Therefore, we adopt a sequential estimation approach as is often used for complex choice models with latent variables (e.g., Haboucha et al., 2017; Yap et al., 2016; Vij et al., 2013).

The estimation procedure consists of two steps: 1) estimating CFA model and output latent factor scores and 2) estimating the MMNL model to get the parameters of interest. In the first step, we fit the ordinal CFA model shown in Fig. 4 using diagonally weighted least squares (DWLS) estimation (Li, 2016; Muthén, 1984), a method specifically designed for CFA estimation with ordinal data, as implemented in the R *lavaan* package (Rosseel, 2012). The method makes no distributional assumptions about the observed ordinal variables, and a normal latent distribution underlying each observed ordinal variable is instead assumed (as described in Section 4.1).

Table 4
Pearson correlation coefficients (ρ) between and variance inflation factors (VIFs) of subjective evaluation and inertia for each travel mode.

	Walk	PT	RH	Drive
ρ: subjective evaluation and lag-term inertia	0.192 ***	−0.016 *	0.129 ***	0.006
ρ: subjective evaluation and hazard-term inertia	0.160 ***	0.045 ***	0.125 ***	0.411 ***
VIF: subjective evaluation	1.467	1.716	1.341	1.249
VIF: lag-term inertia	3.049	3.347	1.755	1.127
VIF: hazard-term inertia	1.709	1.908	1.428	1.582

Then the factor scores for each latent variable and each individual (i.e., $\widehat{A}_{nm}$) are estimated using Eq 3. In the second step, we estimate the MMNL with MSL, obtaining $\boldsymbol{\beta}, \boldsymbol{\sigma}_j$ and μ_{SP}. The model is estimated using PandasBiogeme with 2,000 random draws (Bierlaire, 2018). All input code and results are saved at https://github.com/mbc96325/Mixture-logit-model-for-AV-adoption.

The main models estimated in this paper did not include survey weights. This is because logit models provide unbiased model coefficients regardless of sample representativeness, particularly when all socio-demographic characteristics are included as controls (Bahamonde-Birke and Hanappi, 2016; Efthymiou and Antoniou, 2016). The models were additionally estimated with survey weights as a robustness check, which showed that our main findings were not affected by the unrepresentativeness of our sample (see Appendix B).

5.5. Evaluation scenarios

To explore how both subjective evaluations and inertia affect people's stated preference, particularly the adoption of AMOD, we estimate and compare four models:

- M1 (base): Socioeconomic variables + mode attributes
- M2 (only subjective evaluations): Socioeconomic variables + mode attributes + subjective evaluations
- M3 (only inertia): Socioeconomic variables + mode attributes + inertia
- M4 (subjective evaluations + inertia): Socioeconomic variables + mode attributes + subjective evaluations + inertia

By comparing the coefficients across the four models, the impact of subjective evaluations and inertia on model fit and parameter interpretation can be evaluated both separately and together in the same framework.

6. Results and discussion

In this section, we focus on the results and discussion of the mode choice models incorporating subjective evaluations and inertia. The results of the supporting CFA analysis are shown in Appendix A. We hypothesize that an individual's choice of mode depends on both their subjective evaluations of modes and their existing use of the modes (inertia), which are distinct constructs.

6.1. Correlation between subjective evaluation and inertia

First, we considered whether subjective evaluations and inertia indeed contained different information. Intuitively, if there's high correspondence between people's attitudes and behavior, then these two constructs will measure the same thing. High correlation would not only lead to the inclusion of unnecessary variables, but also introduce multicollinearity problems that affect model estimation and interpretation.

To verify that our measures of subjective evaluation and inertia are distinct variables, we first consider the correlation matrix between them (Table 4). It shows that almost no correlation exists between subjective evaluations and lag inertia (observed choices) for all modes. Slightly higher correlation exists between subjective evaluations and the hazard inertia (stated preference), but the maximum correlation was 0.411 (for driving).

To verify that the correlations will not affect model estimation, the variance inflation factors (VIFs) were estimated (Table 4). The variance inflation factor is a standard measure of multicollinearity, which is the inverse of the R^2 value of the linear regression between the target variable and all other variables. A high VIF means that the target variable can be expressed as a linear combination of all other variables with a strong fit; therefore, multicollinearity problems will follow if all variables are included in model estimation. The common rule of thumb is that a value higher than 5 or 10 indicates severe multicollinearity that needs to be addressed (O'brien 2007). In this case, the highest VIF score is 3.35, which means that no significant multicollinearity problems exist in including both the subjective evaluations and the inertia terms in the choice model. Therefore, we conclude that our measure of subjective evaluations, observed use of existing modes (lag-inertia), and repeated stated preference for a mode (hazard-inertia) can all play different roles in people's mode choice.

6.2. Model fit

To evaluate model fit, four metrics were calculated: log-likelihood, Akaike Information Criterion (AIC), Bayesian Information

Table 5
Results from the unweighted hybrid choice models: unstandardized parameter (standard error).

Parameter	M1 Base	M2 Base + subjective evaluations	M3 Base + inertia	M4 Base + subjective evaluations + inertia
Alternative specific constants (β^{ASC})				
Walk	0.000 (fixed)	0.000 (fixed)	0.000 (fixed)	0.000 (fixed)
Public transport (PT)	−0.147 (0.108)	−0.056 (0.114)	0.690 (0.146) ***	0.761 (0.190) ***
Ridehailing (RH)	−0.616 (0.126) ***	−0.531 (0.126) ***	−0.450 (0.164) ***	−0.412 (0.183) **
Drive	0.103 (0.081)	0.199 (0.083) **	0.027 (0.114)	−0.089 (0.177)
AMOD	−0.697 (0.137) ***	−0.504 (0.147) ***	−0.425 (0.191) **	−0.470 (0.228) **
Subjective evaluations (β_m^A)				
Walk: Pro-walk	–	0.775 (0.065) ***	–	0.863 (0.108) ***
PT: Pro-walk	–	−0.048 (0.046)	–	−0.029 (0.090)
PT: Pro-PT	–	0.698 (0.068) ***	–	0.524 (0.089) ***
RH: Pro-RH	–	0.568 (0.047) ***	–	0.550 (0.069) ***
Drive: Pro-drive	–	0.597 (0.057) ***	–	0.577 (0.116) ***
AMOD: Pro-walk	–	0.027 (0.059)	–	0.184 (0.095) *
AMOD: Pro-PT	–	−0.054 (0.081)	–	−0.098 (0.088)
AMOD: Pro-RH	–	0.416 (0.050) ***	–	0.386 (0.071) ***
AMOD: Pro-drive	–	0.039 (0.053)	–	−0.055 (0.075)
Inertia (lagged β_j^L and hazard β_j^H)				
Walk: Lag inertia-walk	–	–	−0.485 (0.089) ***	−0.592 (0.110) ***
Walk: Hazard inertia-walk	–	–	0.813 (0.079) ***	0.831 (0.096) ***
PT: Lag inertia-walk	–	–	−0.926 (0.090) ***	−1.200 (0.146) ***
PT: Hazard inertia-walk	–	–	0.222 (0.052) ***	0.194 (0.067) ***
PT: Lag inertia-PT	–	–	−0.979 (0.072) ***	−1.340 (0.138) ***
PT: Hazard inertia-PT	–	–	0.780 (0.073) ***	1.200 (0.155) ***
RH: Lag inertia-RH	–	–	1.110 (0.106) ***	1.230 (0.147) ***
RH: Hazard inertia-RH	–	–	0.772 (0.085) ***	0.944 (0.127) ***
Drive: Lag inertia-drive	–	–	0.201 (0.367)	0.240 (0.591)
Drive: Hazard inertia-drive	–	–	1.330 (0.136) ***	2.430 (0.377) ***
AMOD: Lag inertia-walk	–	–	0.000 (fixed)	0.000 (fixed)
AMOD: Hazard inertia-walk	–	–	−0.120 (0.066) *	−0.100 (0.070)
AMOD: Lag inertia-PT	–	–	0.364 (0.091) ***	0.404 (0.106) ***
AMOD: Hazard inertia-PT	–	–	0.074 (0.044) *	0.101 (0.052) *
AMOD: Lag inertia-RH	–	–	1.410 (0.140) ***	1.600 (0.191) ***
AMOD: Hazard inertia-RH	–	–	0.507 (0.072) ***	0.665 (0.106) ***
AMOD: Lag inertia-drive	–	–	0.764 (0.247) ***	0.702 (0.281) **
AMOD: Hazard inertia-drive	–	–	0.157 (0.102)	0.254 (0.124) **
Mode attributes (β_T)				
Walk: Walking time (min)	−0.050 (0.003) ***	−0.050 (0.003) ***	−0.046 (0.003) ***	−0.054 (0.004) ***
PT: Travel cost ($SG)	−0.221 (0.018) ***	−0.240 (0.021) ***	−0.278 (0.024) ***	−0.396 (0.046) ***
PT: In-vehicle time (min)	−0.020 (0.001) ***	−0.020 (0.001) ***	−0.022 (0.002) ***	−0.027 (0.003) ***
PT: Waiting time (min)	−0.031 (0.004) ***	−0.031 (0.004) ***	−0.034 (0.005) ***	−0.043 (0.008) ***
PT: Walking time (min)	−0.034 (0.003) ***	−0.035 (0.003) ***	−0.035 (0.003) ***	−0.047 (0.005) ***
RH: Travel cost ($SG)	−0.061 (0.005) ***	−0.065 (0.005) ***	−0.073 (0.006) ***	−0.092 (0.009) ***
RH: In-vehicle time (min)	−0.028 (0.003) ***	−0.030 (0.003) ***	−0.032 (0.004) ***	−0.046 (0.006) ***
RH: Waiting time (min)	−0.042 (0.007) ***	−0.036 (0.006) ***	−0.036 (0.008) ***	−0.039 (0.009) ***
Drive: Travel cost ($SG)	−0.116 (0.007) ***	−0.110 (0.007) ***	−0.109 (0.007) ***	−0.149 (0.016) ***
Drive: In-vehicle time (min)	−0.040 (0.004) ***	−0.042 (0.004) ***	−0.046 (0.005) ***	−0.064 (0.009) ***
Drive: Walking time (min)	−0.054 (0.011) ***	−0.051 (0.010) ***	−0.038 (0.013) ***	−0.062 (0.021) ***
AV: Travel cost ($SG)	−0.094 (0.006) ***	−0.096 (0.006) ***	−0.113 (0.008) ***	−0.132 (0.012) ***
AV: In-vehicle time (min)	−0.033 (0.003) ***	−0.034 (0.003) ***	−0.039 (0.004) ***	−0.049 (0.005) ***
AV: Waiting time (min)	−0.043 (0.007) ***	−0.040 (0.006) ***	−0.045 (0.008) ***	−0.051 (0.009) ***
Individual characteristics (β_X)				
PT: Income[1] < SG$ 4,000	0.096 (0.054) *	0.129 (0.056) **	0.099 (0.067)	0.190 (0.089) **
PT: Income[1] > SG$ 12,000	−0.002 (0.071)	−0.032 (0.073)	0.041 (0.087)	0.025 (0.111)
PT: Single	0.052 (0.063)	0.068 (0.065)	0.126 (0.079)	0.208 (0.104) **
PT: Driver license	−0.190 (0.051) ***	−0.171 (0.054) ***	−0.139 (0.063) **	−0.161 (0.083) *
PT: Chinese	−0.013 (0.064)	−0.007 (0.067)	−0.010 (0.080)	0.032 (0.104)
PT: Commute trip	0.727 (0.062) ***	0.725 (0.066) ***	0.700 (0.079) ***	0.955 (0.126) ***
PT: Full-time job	0.063 (0.052)	0.051 (0.054)	0.013 (0.064)	0.005 (0.084)
PT: High education[2]	0.107 (0.049) **	0.069 (0.051)	0.089 (0.061)	0.043 (0.079)
PT: Age > 60	−0.013 (0.096)	−0.094 (0.100)	−0.014 (0.120)	−0.120 (0.158)
PT: Age < 35	0.113 (0.054) **	0.025 (0.056)	0.031 (0.067)	−0.091 (0.088)
PT: Car owner	0.066 (0.129)	0.079 (0.134)	−0.113 (0.153)	−0.224 (0.195)
PT: Male	−0.037 (0.047)	−0.021 (0.048)	−0.013 (0.058)	0.003 (0.075)
PT: Have kid under 18	−0.029 (0.065)	−0.014 (0.068)	0.004 (0.081)	0.008 (0.105)
RH: Income < SG$ 4,000	−0.121 (0.065) *	−0.070 (0.064)	−0.072 (0.079)	−0.023 (0.086)
RH: Income > SG$ 12,000	0.170 (0.081) **	0.127 (0.081)	0.127 (0.098)	0.108 (0.108)

(continued on next page)

Table 5 (*continued*)

Parameter	M1 Base	M2 Base + subjective evaluations	M3 Base + inertia	M4 Base + subjective evaluations + inertia
RH: Single	−0.111 (0.075)	−0.085 (0.074)	−0.008 (0.091)	0.032 (0.100)
RH: Driver license	−0.291 (0.061) ***	−0.225 (0.060) ***	−0.268 (0.074) ***	−0.216 (0.082) ***
RH: Chinese	−0.371 (0.073) ***	−0.342 (0.073) ***	−0.302 (0.089) ***	−0.311 (0.098) ***
RH: Commute trip	0.346 (0.060) ***	0.350 (0.060) ***	0.475 (0.079) ***	0.551 (0.093) ***
RH: Full-time job	0.207 (0.063) ***	0.169 (0.062) ***	0.152 (0.076) **	0.124 (0.084)
RH: High education	0.134 (0.058) **	0.064 (0.058)	0.117 (0.071) *	0.052 (0.078)
RH: Age > 60	−0.045 (0.120)	−0.027 (0.120)	−0.014 (0.146)	−0.020 (0.163)
RH: Age < 35	0.366 (0.066) ***	0.225 (0.065) ***	0.285 (0.079) ***	0.183 (0.086) **
RH: Car owner	0.558 (0.142) ***	0.658 (0.143) ***	0.303 (0.167) *	0.427 (0.184) **
RH: Male	−0.185 (0.057) ***	−0.177 (0.056) ***	−0.081 (0.069)	−0.090 (0.075)
RH: Have kid under 18	0.170 (0.077) **	0.211 (0.077) ***	0.203 (0.094) **	0.287 (0.105) ***
Drive: Income < SG$ 4,000	−0.151 (0.098)	−0.121 (0.100)	−0.003 (0.132)	0.086 (0.203)
Drive: Income > SG$ 12,000	0.144 (0.084) *	0.142 (0.084) *	0.157 (0.108)	0.259 (0.157) *
Drive: Single	0.089 (0.093)	0.165 (0.093) *	0.065 (0.124)	0.223 (0.188)
Drive: Driver license	0.103 (0.081)	0.199 (0.083) **	0.027 (0.114)	−0.089 (0.177)
Drive: Chinese	−0.082 (0.105)	−0.138 (0.106)	−0.120 (0.141)	−0.242 (0.211)
Drive: Commute trip	0.427 (0.073) ***	0.396 (0.074) ***	0.480 (0.101) ***	0.619 (0.154) ***
Drive: Full-time job	−0.034 (0.078)	−0.074 (0.079)	0.006 (0.105)	−0.017 (0.160)
Drive: High education	0.038 (0.070)	0.016 (0.070)	−0.016 (0.093)	−0.104 (0.140)
Drive: Age > 60	−0.035 (0.136)	−0.119 (0.139)	−0.019 (0.184)	−0.155 (0.278)
Drive: Age < 35	0.223 (0.079) ***	0.174 (0.080) **	0.123 (0.105)	0.075 (0.159)
Drive: Car owner	0.411 (0.137) ***	0.478 (0.140) ***	0.218 (0.171)	0.314 (0.236)
Drive: Male	−0.036 (0.065)	−0.063 (0.066)	−0.001 (0.087)	0.015 (0.131)
Drive: Have kid under 18	0.074 (0.089)	0.093 (0.089)	0.095 (0.119)	0.160 (0.177)
AV: Income < SG$ 4,000	−0.110 (0.070)	−0.064 (0.069)	−0.062 (0.084)	−0.015 (0.094)
AV: Income > SG$ 12,000	0.100 (0.086)	0.061 (0.086)	0.067 (0.103)	0.053 (0.115)
AV: Single	−0.126 (0.081)	−0.114 (0.080)	−0.066 (0.097)	−0.065 (0.107)
AV: Driver license	−0.058 (0.065)	−0.032 (0.067)	−0.037 (0.079)	0.028 (0.091)
AV: Chinese	−0.170 (0.080) **	−0.166 (0.080) **	−0.109 (0.097)	−0.112 (0.107)
AV: Commute trip	0.479 (0.066) ***	0.448 (0.065) ***	0.447 (0.083) ***	0.478 (0.095) ***
AV: Full-time job	0.222 (0.068) ***	0.187 (0.068) ***	0.174 (0.082) **	0.165 (0.092) *
AV: High education	0.177 (0.063) ***	0.123 (0.062) **	0.147 (0.076) *	0.118 (0.085)
AV: Age > 60	−0.018 (0.130)	−0.017 (0.130)	−0.031 (0.157)	−0.013 (0.175)
AV: Age < 35	0.476 (0.072) ***	0.327 (0.070) ***	0.383 (0.086) ***	0.298 (0.095) ***
AV: Car owner	0.228 (0.154)	0.318 (0.156) **	−0.015 (0.181)	0.083 (0.202)
AV: Male	−0.045 (0.060)	−0.039 (0.059)	0.082 (0.072)	0.091 (0.080)
AV: Have kid under 18	0.214 (0.082) ***	0.238 (0.082) ***	0.230 (0.100) **	0.298 (0.112) ***
Others				
SP scale[3] (μ_{SP})	1.390 (0.073) ***	1.440 (0.075) ***	1.210 (0.070) ***	1.160 (0.094) *
Walk: HFP[4] (γ_k)	–	–	0.364 (0.063) ***	0.332 (0.069) ***
PT: HFP (γ_k)	–	–	0.222 (0.049) ***	0.258 (0.045) ***
RH: HFP (γ_k)	–	–	0.247 (0.099) **	0.283 (0.104) ***
Drive: HFP (γ_k)	–	–	0.590 (0.070) ***	0.607 (0.063) ***
PT: Std. Dev. [5] (σ_j)	–	0.486 (0.138) ***	–	1.390 (0.209) ***
RH: Std. Dev. (σ_j)	–	0.003 (0.136)	–	0.010 (0.123)
Drive: Std. Dev. (σ_j)	–	0.009 (0.109)	–	1.770 (0.310) ***
AV: Std. Dev. (σ_j)	–	0.001 (0.075)	–	0.000 (0.088)
Statistical summary				
Final log-likelihood	−12299.32	−11983.09	−10389.58	−10236.7
AIC	24740.65	24134.19	20963.17	20683.40
BIC	25263.20	24752.42	21640.28	21456.19
ρ^2	0.266	0.285	0.380	0.389
Adjusted ρ^2	0.262	0.280	0.375	0.383

*: p-value < 0.10; **: p-value < 0.05; ***: p-value < 0.01;
5: "Std. Dev." means standard deviation.
For all models, results were estimated from a sample of 2,003 individuals, 11,613 choice observations, with an initial log-likelihood of −16764.55.
1 : "Income" means household monthly income.
2 : "High education" means with Bachelor's degree or higher.
3 : The p-value for μ_{SP} is tested against 1 instead of 0 (using *t*-test) because μ_{RP} is normalized to 1. μ_{SP} in all models are>1, meaning RP responses contain more random noise than SP responses (Polydoropoulou and Ben-Akiva, 2001).
4 : "HFP" means hazard function parameter.

Criterion (BIC), and adjusted ρ^2. The values are presented in the bottom panel of Table 5. For all metrics, model performances improved from M1 to M4, meaning both subjective evaluations and inertia improved the explanatory power of the model. Among the improvements, M3 and M4 were significantly better than M1 and M2. Although both helped to improve the model fit, the actual choices (represented by inertia) can better model people's stated preferences than their subjective evaluations of the alternatives. Nevertheless, M4 was better than M3 along all dimensions; therefore, subjective evaluations did play a role in the respondents' stated preferences. Further, the parameters estimated for the explanatory variables (subjective evaluations, inertia, sociodemographic variables, and except for alternative-specific constants) had the same sign and similar magnitudes in all models. Therefore, the results from M4 in which all factors were included are discussed in the following sections.

6.3. Inertia

Here we consider the impact of our inertia terms on people's stated preference for AMOD or other modes. The lagged inertia variable indicates familiarity (previous use) of the mode and the hazard inertia variable represents the repeated choice of the mode under different choice scenarios. Including both inertia terms significantly improves model performance, even when including them in the same model as the subjective evaluations of existing modes (M4).

We start with a discussion of the lagged inertia variables. For existing modes, greater familiarity from use of the existing mode did not always lead to a greater likelihood of choosing it in the hypothetical choice scenarios. For ridehailing (and, not significantly, driving), the coefficient for lagged inertia is positive, suggesting that the users of these current modes were more likely to continue using them. In other words, respondents that are currently using car-based modes are doing so by choice. On the other hand, the choices to walk or take public transit were negatively predicted by existing use of those modes. Individuals who were walking and taking public transit tended to switch modes if a better alternative was presented in their stated preference choice sets. This result might suggest that individuals currently walk or take public transit in Singapore because they lacked an affordable or easy alternative rather than because it is their true preference.

Considering likelihood to switch to AMOD from existing modes, we found that users with greater lag inertia for ridehailing were the most likely to switch to AMOD, followed by driving, public transit, and then walking. All else being equal, individuals who currently use ridehailing and drive their personal car were the most likely to switch to AMOD when it becomes available, with coefficients of lag inertia of 1.600 and 0.702, respectively. This could indicate that individuals are more likely to adopt a new AMOD when it is similar to what they already use to travel—e.g., ridehailing, or to a lesser extent, driving a car. Cai et al. (2019) reached similar conclusions by estimating AV choice models separately for Singaporean drivers and transit users.

All hazard inertia coefficients for the existing modes are statistically significant and positive, meaning that people tend to choose one mode repeatedly when presented with different choice scenarios. This may be reflective of an anchoring effect where people are overly reliant on the first piece of information for decision-making and evaluate latter scenarios with respect to the previous ones. In other words, respondents may have related subsequent choice scenarios to a previous one, deciding whether to switch from the previous choice. For the choice of switching to AMOD we again find an effect similar to lagged inertia, where people who previously chose ridehailing in the choice experiments were the most likely to switch to AMOD in subsequent choice scenarios. The coefficient for hazard inertia is strongly positive for ridehailing and negative for walking. The hazard inertia terms for both driving and public transit were not consistently statistically different from zero across the weighted and unweighted models (see Appendix B).

6.4. Subjective evaluations of existing travel modes (Attitudes)

Additionally, we consider how the subjective evaluation of existing travel modes—in terms of their safety, comfort, reliability, enjoyment, and ease of use—influence the choice of AMOD over other modes of travel. Including these subjective evaluations produces a smaller, but still statistically significant improvement on model fit beyond inertia and other individual- and mode-specific attributes (comparing M4 to M3). This indicates that subjective evaluations of existing modes offer behavioral insights into mode choice decision making separate and in addition to existing use of those modes.

In general, we find that positive evaluations of an existing mode contribute to a greater likelihood of choosing that mode. For example, those who had stronger positive evaluations of walking, public transit, ridehailing, and driving were more likely to choose these modes. Subjective evaluations of existing modes are less predictive of stated preference towards a new travel mode, in our case AMOD. M4 finds that an individual's subjective evaluations of driving and public transit do not significantly influence choice to use AMOD, while having a positive attitude towards ridehailing and walking is a significant predictor of choosing AMOD (see also weighted model results in Appendix B). Since ridehailing, being a chauffeured mobility-on-demand service, is the most similar to our hypothetical AMOD mode in terms of its trip attributes, this finding might suggest that positive evaluations of existing services that were similar to in terms of service design may help to predict adoption of new technologies. However, this positive relationship between ridehailing attitudes and AMOD choice may alternatively be due to other shared predictors not captured in the model, such as an individual's familiarity with smartphone apps, propensity or interest in using new technologies in general, or other factors.

Since subjective evaluations matter in decision making and it is difficult to ask for people's evaluations on something not implemented, close neighbors to new technologies might be used as proxies to evaluate people's likely reactions towards and identify potential adopters of new transportation modes or technologies. But the choice of proxy is not a trivial issue; it depends not only on the technology itself, but also on how the technology will be implemented within the mobility system.

6.5. Socio-demographic variables and mode attributes

Finally, we briefly discuss the estimated parameters for the socio-demographic characteristics of travelers ($\boldsymbol{\beta}_X$) and mode attributes ($\boldsymbol{\beta}_T$) for M4 shown in Table 5.

Table 6
Values of time estimated from M4.

	PT	RH	Drive	AMOD
Value of in-vehicle time (S$/min)	4.1	30.0	25.8	22.3
Value of waiting time (S$/min)	6.5	25.4	–	23.2
Value of walk time (S$/min)	7.12	–	25.0	–

6.5.1. Mode-Specific attributes

When it comes to mode-specific attributes, we find that all travel time and cost related variables have negative coefficients, as expected, and are statistically different from zero with p-value < 0.01. We can also use these coefficients to estimate values of in-vehicle, waiting, and walking time for our different mode choices (Table 6).

Comparing the cost and in-vehicle time coefficients across modes, we find that individuals are the most sensitive to PT travel cost and least sensitive to PT travel time—suggesting that people take public transport with the expectation that it is not time-efficient. From the estimated coefficients for AMOD, we see that individuals are expecting this service to be time-efficient. We also find that the choice to take AMOD or ridehailing is more sensitive to waiting time than public transit. Finally, we find that the value of walking time for driving is similar in magnitude to the value of waiting time for both AMOD and ridehailing.

6.5.2. Characteristics of travelers

The effects of traveler characteristics are included in the utility functions for PT, RH, drive, and AMOD, with walking treated as the reference mode. Here we discuss the coefficients from M4 that were found to be significant at a 95% confidence level (see Table 5). Where possible, we compare our results to the literature in general and specifically to the findings from Cai et al. (2019), which presents results from a similar survey conducted in at similar time and in the same location—i.e., Singapore.

We find that income is not a significant predictor of AMOD choice, although the coefficient is positive suggesting that individuals with higher income may be more willing to adopt AVs, which is consistent with findings from Liu et al. (2019) and Shabanpour et al. (2018). Similar to Cai et al. (2019), we find that having a lower income is a significant predictor of greater transit use in our sample of Singaporean residents. While we see no significant impact of income on AMOD choice, we do find that related sociodemographic characteristic of employment is predictive. People with a full-time job are found to be more likely to take ridehailing (similar to findings by Moody and Zhao, 2020) and AMOD. When it comes to the effect of education on AV mode choice, some studies have found education to be a significant predictor (Liu et al., 2019; Bansal et al., 2016) while others have found either insignificant effect (Zmud and Sener, 2017) or mixed effects for different forms of AV (Cai et al., 2019). In our study we find that high education level is a positive, but not significant indicator of AMOD adoption after controlling for subjective evaluation and use of existing modes.

When it comes to age, gender, and ethnicity, we find that younger people have a greater inclination towards ridehailing and AMOD (in line with Cai et al., 2019; Liu et al., 2019; Shabanpour et al., 2018) as well as driving. Gender is not found to be a significant predictor of mode choice, whereas people who self-report as Chinese ethnicity are less likely to take ridehailing and AMOD.

As expected, we find that people with a driver's license are more likely to drive than walk and less likely to take ridehailing or public transit. It is not a significant predictor of AMOD choice. Relatedly, having more cars in the household predicts greater choice of driving and ridehailing. The finding that car ownership is positively predictive of ridehailing adoption has been observed in other survey studies in Singapore (Moody and Zhao, 2020) and may reflect the fact that car owners are accustomed to traveling with car-based modes. Car ownership, like having a driver's license, is not significantly predictive of AMOD choice.

Finally, when it comes to trip purpose, we find that all modes are preferred over walking for commuting trips, with the most preferred mode being public transport.

7. Conclusion

This paper studied how subjective evaluations and inertia from use of existing modes affect individual choices on AMOD adoption using a combined revealed and stated preference survey. To obtain subjective evaluations, the respondents were asked to rate on a 7-point Likert scale their impressions of the existing modes based on safety, comfort, reliability, enjoyment, and ease of use. A confirmatory factor analysis was performed to obtain the subjective evaluations of existing modes. In addition, use of existing modes for a given trip from the revealed preference portion and from repeated selection in the stated preference portion of the survey were included in the choice model as modal inertia terms, measuring a respondent's tendency to stick to their current mode of travel. A mixed logit choice model was estimated to investigate how subjective evaluations and use of existing modes separately and simultaneously affect individuals' mode choice when a new autonomous mobility-on-demand (AMOD) service is introduced.

We found that subjective evaluations and past mode use are related, but distinct constructs that jointly influence people's future mode choices. In general, we found that individuals who have positive subjective evaluations of a given mode are more likely to choose it for their trip and that, even controlling for these attitudes and other individual- and mode-specific attributes, there is indeed significant inertia in mode choice.

When it comes to modeling the adoption of a new, hypothetical AMOD service, we find that individuals with positive attitudes towards and existing use of car-based modes that are similar to the new AV service are more likely to switch to AMOD. In particular, we found that people with a positive evaluation of ridehailing and those that are currently ridehailing users are the most likely to choose AMOD. Additionally, those who are current car drivers are more likely to choose AMOD, while users of public transit were less likely to choose AMOD. Given that ridehailing is the closest existing mode to our hypothetical AMOD service, our results might suggest that how AVs are implemented and their similarity to existing modes may be critical to the formation of attitudes and direction of inertia impacting adoption. However, future work is needed to further explore the substitutability between existing, chauffeured ridehailing services and new AMOD services.

This finding may have significant implications for how we predict adoption of and design service for AVs. We find that subjective evaluations of existing modes provide useful information only when the proposed implementation is similar enough to an existing mode. When we measure people's acceptance of new technologies, contexts that relate to the individual's perceptions and use of existing travel options can help to solicit meaningful intentions. On the other hand, interactions with existing modes, represented by inertia, provide more information on whether people will choose the newly introduced travel mode. The study found that people familiar with mobility options that are already similar to the newly proposed mode had a greater tendency to switch. Here we caution that the purpose of our model is in describing rather than predicting adoption of AV services. If our model were to be used for prediction, further model calibration and appropriate weighting of the sample to be representative of the Singaporean population would likely be necessary.

While this work contributes to existing understanding of user adoption of autonomous vehicle technology and extends the state-of-practice on mode choice modeling with latent variables and inertial terms, there remain many areas for future research. For example, our study only considered one form of AV implementation, namely an autonomous mobility-on-demand service. Since we found that both subjective evaluations and inertia from use of existing modes are most influential when the existing mode is very similar to the new mode introduced in the choice experiment, it could be interesting to study these same research questions for other forms of AV deployment, such as private ownership or autonomous public transit. The impact of subjective evaluations and inertia on different AV implementations may corroborate or challenge the interpretation of the model results presented in this study. Furthermore, research could consider how subjective evaluation and current use of existing travel modes influence AV choice in other settings or for specific groups of individuals (perhaps using latent classes), thereby helping to generalize the findings from this study to other geographies or target populations of interest. Finally, as AV technology matures and becomes commercially available in the mobility market, it will be important to observe actual user adoption of these services and compare these revealed preferences with previous stated preference studies.

CRediT authorship contribution statement

Baichuan Mo: Data curation, Methodology, Formal analysis, Writing – original draft, Writing – review & editing. **Qing Yi Wang:** Writing – original draft, Writing – review & editing. **Joanna Moody:** Project administration, Formal analysis, Writing – original draft, Writing – review & editing. **Yu Shen:** Conceptualization, Data curation. **Jinhua Zhao:** Conceptualization, Funding acquisition, Supervision.

Acknowledgement

This study is supported by Natural Science Foundation of Shanghai (19ZR1460700) and the Fundamental Research Funds for the Central Universities (22120180569). The research is also supported by the National Research Foundation, the Prime Minister's Office of Singapore under the CREATE program, and the SMART's Future Urban Mobility IRG. The survey has been approved by MIT's Committee on the Use of Humans as Experimental Subjects under Protocol 1609690311.

Appendix. A: Results of confirmatory factor analysis

Convergent validity

For each latent variable, we follow the same process to demonstrate that the survey items that measure the same construct are indeed highly related (convergent validity). We begin by estimating a baseline confirmatory factor analysis model with all survey items loading onto a single factor. To ensure convergent validity, we want the majority of the item variances to be explained by the single factor (standardized factor loading of > 0.70 and an $R^2 > 0.5$) as suggested by (Kline, 2016). While this threshold was not met for all items, they did meet a more practical cut-off of 0.45 and no items showed factor loading that were so poor they warranted removing from the model entirely. This also means that the characteristics/items that make up the subjective evaluation latent variable are the same for each of the four modes (see Table A1).

We also compare the overall model fit to established standards: a chi-square test statistic that is not statistically different from zero, CFI and TLI$>$0.90, and RMSEA and SRMR$<$0.08 (Kline, 2016) (see Table A2). If the model does not meet established standards of model fit, then we investigate Lagrangian Multiplier modification indices (MIs). We review each pair of items for which MIs are high, indicating that introducing a correlation between their error terms could significantly improve the chi-square of the model. If needed, correlated error terms were added one by one and each time we re-estimated the model and check the factor loadings, model fit, and MIs. Only one model, the model for pro-walk subjective evaluations, warranted the inclusion of a correlated error term between the indicators for safety and reliability (see Table A1).

Table A1
Standardized factor loadings and R^2 values for CFA models (estimated separately for each subjective evaluation factor).

Factor	Indicator	Standardized factor loading	R^2
Pro-walk	I think walking feels safe	0.511	0.261
	I think walking is comfortable	0.678	0.460
	I think walking is a reliable mode	0.728	0.530
	I think walking feels easy	0.792	0.628
	I enjoy walking	0.895	0.802
	correlation between errors for safe and reliable	0.336	–
Pro-PT	I think taking public transport feels safe	0.532	0.283
	I think taking public transport is comfortable	0.675	0.456
	I think public transport is a reliable mode	0.763	0.581
	I think taking public transport is easy	0.720	0.519
	I enjoy taking public transport	0.898	0.807
Pro-RH	I think ridehailing feels safe	0.686	0.470
	I think ridehailing is comfortable	0.769	0.592
	I think ridehailing is a reliable mode	0.816	0.665
	I think ridehailing is easy	0.758	0.575
	I enjoy ridehailing	0.811	0.658
Pro-drive	I think driving feels safe	0.655	0.429
	I think driving is comfortable	0.794	0.630
	I think driving is a reliable mode	0.821	0.675
	I think driving is easy	0.872	0.761
	I enjoy driving	0.864	0.747

Note: All factor loadings for all models were found to be statistically significant at the 1% level.

Table A2
Robust model fit statistics for the estimated CFA models.

Model	X^2, p-value	CFI	TLI	RMSEA	SRMR
Pro-walk: Baseline + correlated error	28.205, 0.000	0.995	0.988	0.055	0.032
Pro-PT: Baseline	33.510, 0.000	0.996	0.993	0.053	0.037
Pro-RH: Baseline	30.188, 0.674	0.998	0.996	0.050	0.023
Pro-drive: Baseline	3.037, 0.694	1.000	1.000	0.000	0.012

Divergent validity

Having established the convergent validity of our latent variables, we now want to ensure that they collectively demonstrate reasonable divergent (or discriminant) validity. We run a CFA model simultaneously estimating the final specifications of all of our latent variables and allowing them to correlate. We are looking to show that items presumed to measure a certain latent variable do not have significant cross-loadings with other latent variable. We only estimate this combined CFA model for the subset of respondents

This combined CFA model demonstrates moderately acceptable model fit across multiple indices: $\chi^2(N = 953, df = 163) = 3966.99$, $p < .01$, CFI = 0.917, TLI = 0.904, RMSEA = 0.075 with 90% CI [0.072, 0.078], and SRMR = 0.096. Of particular interest for discriminant validity is the correlations among the latent variables given in Table A3. We find these correlations range between 0.288 and 0.737, suggested that they are related, but distinct variables.

We additionally consider the MIs among the latent variables and their indicators. We find that there are only a few MIs large enough to suggest potential cross-loading of indicators among latent variables. However, given the moderate model fit without these cross-loadings, we do not include them when estimating the correlations above.

Table A3
Correlations among the subjective evaluations (latent variables) of the different modes.

	Walk	PT	RH	Drive
Walk	1.000			
PT	0.737	1.000		
RH	0.288	0.589	1.000	
Drive	0.314	0.326	0.442	1.000

Reliability

Finally, we estimate three common reliability indices for our latent variables: Cronbach's alpha (α), composite reliability (or Ω) and maximal reliability (H). For these reliability calculations, we treat our ordinal 7-point Likert scale indicators as a continuous as an approximation. We find that our latent variables show strong internal consistency (α), composite reliability, and maximal reliability, with all indices above 0.7 (Kline, 2016) as shown in Table A4.

Table A4
Reliability indices for the estimated latent variables.

Latent variable (SE)	Cronbach's alpha (α)	Composite reliability (Ω)	Maximal reliability (H)
Walking	0.908	0.898	0.905
PT	0.875	0.876	0.889
RH	0.804	0.805	0.822
Drive	0.886	0.869	0.891

Appendix B. Model estimation results with sample weights

Table B1 presents complete results from the hybrid choice models estimated including sample weights calculated to adjust for non-representativeness of the survey sample.

Table B1
Results from the weighted hybrid choice models: unstandardized parameter (standard error).

Parameter	M1 Base	M2 Base + subjective evaluations	M3 Base + inertia	M4 Base + subjective evaluations + inertia
Alternative specific constants (β^{ASC})				
Walk	0.000 (fixed)	0.000 (fixed)	0.000 (fixed)	0.000 (fixed)
Public transport (PT)	−0.398 (0.110) ***	−0.325 (0.110) ***	0.545 (0.130) ***	0.454 (0.161) ***
Ridehailing (RH)	−0.829 (0.127) ***	−0.610 (0.124) ***	−0.571 (0.143) ***	−0.543 (0.166) ***
Drive	0.163 (0.112)	0.405 (0.110) ***	0.116 (0.133)	0.098 (0.216)
AMOD	−0.992 (0.147) ***	−0.835 (0.161) ***	−0.721 (0.178) ***	−0.773 (0.229) ***
Subjective evaluations (β_m^A)				
Walk: Pro-walk	–	1.060 (0.075) ***	–	0.891 (0.107) ***
PT: Pro-walk	–	0.077 (0.055)	–	0.126 (0.080)
PT: Pro-PT	–	0.638 (0.053) ***	–	0.499 (0.085) ***
RH: Pro-RH	–	0.619 (0.046) ***	–	0.588 (0.071) ***
Drive: Pro-drive	–	0.544 (0.069) ***	–	0.446 (0.139) ***
AMOD: Pro-walk	–	0.141 (0.077) *	–	0.272 (0.093) ***
AMOD: Pro-PT	–	−0.009 (0.077)	–	−0.078 (0.092)
AMOD: Pro-RH	–	0.426 (0.052) ***	–	0.374 (0.072) ***
AMOD: Pro-drive	–	−0.103 (0.068)	–	−0.056 (0.086)
Inertia (lagged β_j^L and hazard β_j^H)				
Walk: Lag inertia-walk	–	–	−0.440 (0.081) ***	−0.534 (0.102) ***
Walk: Hazard inertia-walk	–	–	0.880 (0.079) ***	0.913 (0.099) ***
PT: Lag inertia-walk	–	–	−1.010 (0.088) ***	−1.130 (0.138) ***
PT: Hazard inertia-walk	–	–	0.270 (0.054) ***	0.266 (0.067) ***
PT: Lag inertia-PT	–	–	−0.942 (0.068) ***	−1.110 (0.124) ***
PT: Hazard inertia-PT	–	–	0.797 (0.071) ***	1.080 (0.157) ***
RH: Lag inertia-RH	–	–	1.160 (0.103) ***	1.180 (0.138) ***
RH: Hazard inertia-RH	–	–	0.748 (0.081) ***	0.911 (0.135) ***
Drive: Lag inertia-drive	–	–	0.182 (0.310)	0.160 (0.549)
Drive: Hazard inertia-drive	–	–	1.210 (0.143) ***	2.450 (0.500) ***
AMOD: Lag inertia-walk	–	–	0.000 (fixed)	0.000 (fixed)
AMOD: Hazard inertia-walk	–	–	−0.108 (0.067)	−0.110 (0.074)
AMOD: Lag inertia-PT	–	–	0.374 (0.087) ***	0.403 (0.104) ***
AMOD: Hazard inertia-PT	–	–	0.019 (0.044)	0.043 (0.051)
AMOD: Lag inertia-RH	–	–	1.240 (0.138) ***	1.310 (0.177) ***
AMOD: Hazard inertia-RH	–	–	0.571 (0.074) ***	0.712 (0.119) ***
AMOD: Lag inertia-drive	–	–	0.819 (0.182) ***	0.851 (0.217) ***
AMOD: Hazard inertia-drive	–	–	0.016 (0.119)	0.067 (0.150)
Mode attributes (β_T)				
Walk: Walking time (min)	−0.058 (0.003) ***	−0.055 (0.003) ***	−0.046 (0.003) ***	−0.053 (0.004) ***
PT: Travel cost ($SG)	−0.247 (0.019) ***	−0.245 (0.018) ***	−0.261 (0.022) ***	−0.346 (0.045) ***

(*continued on next page*)

Table B1 (*continued*)

Parameter	M1 Base	M2 Base + subjective evaluations	M3 Base + inertia	M4 Base + subjective evaluations + inertia
PT: In-vehicle time (min)	−0.023 (0.001) ***	−0.022 (0.001) ***	−0.024 (0.002) ***	−0.028 (0.003) ***
PT: Waiting time (min)	−0.022 (0.004) ***	−0.020 (0.004) ***	−0.021 (0.005) ***	−0.025 (0.006) ***
PT: Walking time (min)	−0.030 (0.002) ***	−0.027 (0.002) ***	−0.029 (0.003) ***	−0.035 (0.004) ***
RH: Travel cost ($SG)	−0.047 (0.004) ***	−0.049 (0.004) ***	−0.054 (0.005) ***	−0.066 (0.007) ***
RH: In-vehicle time (min)	−0.037 (0.004) ***	−0.039 (0.004) ***	−0.039 (0.004) ***	−0.051 (0.006) ***
RH: Waiting time (min)	−0.043 (0.007) ***	−0.036 (0.006) ***	−0.029 (0.007) ***	−0.036 (0.009) ***
Drive: Travel cost ($SG)	−0.140 (0.008) ***	−0.129 (0.007) ***	−0.115 (0.008) ***	−0.163 (0.022) ***
Drive: In-vehicle time (min)	−0.037 (0.005) ***	−0.041 (0.005) ***	−0.045 (0.006) ***	−0.064 (0.011) ***
Drive: Walking time (min)	−0.097 (0.018) ***	−0.086 (0.018) ***	−0.068 (0.021) ***	−0.102 (0.035) ***
AV: Travel cost ($SG)	−0.083 (0.006) ***	−0.081 (0.005) ***	−0.085 (0.006) ***	−0.099 (0.010) ***
AV: In-vehicle time (min)	−0.040 (0.004) ***	−0.040 (0.003) ***	−0.041 (0.004) ***	−0.050 (0.006) ***
AV: Waiting time (min)	−0.061 (0.008) ***	−0.055 (0.007) ***	−0.050 (0.008) ***	−0.059 (0.010) ***
Individual characteristics (β_X)				
PT: Income[1] < SG$ 4,000	0.173 (0.059) ***	0.184 (0.058) ***	0.141 (0.065) **	0.225 (0.086) ***
PT: Income[1] > SG$ 12,000	0.072 (0.067)	0.041 (0.066)	0.077 (0.072)	0.069 (0.087)
PT: Single	0.135 (0.065) **	0.133 (0.063) **	0.165 (0.072) **	0.253 (0.095) ***
PT: Driver license	−0.219 (0.055) ***	−0.077 (0.053)	−0.121 (0.059) **	−0.040 (0.072)
PT: Chinese	−0.106 (0.059) *	−0.072 (0.058)	−0.114 (0.065) *	−0.094 (0.079)
PT: Commute trip	0.638 (0.057) ***	0.565 (0.055) ***	0.436 (0.061) ***	0.569 (0.097) ***
PT: Full-time job	0.246 (0.055) ***	0.147 (0.053) ***	0.216 (0.059) ***	0.200 (0.074) ***
PT: High education[2]	0.117 (0.055) **	0.102 (0.053) *	0.031 (0.058)	0.006 (0.071)
PT: Age > 60	−0.020 (0.067)	−0.105 (0.065)	0.088 (0.073)	0.054 (0.090)
PT: Age < 35	0.031 (0.062)	−0.027 (0.061)	−0.003 (0.067)	−0.056 (0.083)
PT: Car owner	0.087 (0.161)	0.154 (0.157)	−0.006 (0.166)	−0.069 (0.201)
PT: Male	0.024 (0.050)	0.036 (0.049)	0.003 (0.054)	−0.014 (0.067)
PT: Have kid under 18	0.068 (0.078)	0.082 (0.076)	0.012 (0.085)	0.031 (0.104)
RH: Income < SG$ 4,000	−0.280 (0.072) ***	−0.242 (0.070) ***	−0.162 (0.075) **	−0.140 (0.085) *
RH: Income > SG$ 12,000	0.281 (0.080) ***	0.193 (0.078) **	0.102 (0.083)	0.049 (0.094)
RH: Single	0.076 (0.078)	0.049 (0.077)	0.179 (0.084) **	0.220 (0.097) **
RH: Driver license	−0.459 (0.068) ***	−0.289 (0.065) ***	−0.292 (0.070) ***	−0.208 (0.079) ***
RH: Chinese	−0.550 (0.071) ***	−0.531 (0.069) ***	−0.366 (0.074) ***	−0.412 (0.087) ***
RH: Commute trip	0.248 (0.061) ***	0.249 (0.060) ***	0.271 (0.065) ***	0.327 (0.077) ***
RH: Full-time job	0.086 (0.065)	−0.013 (0.064)	0.146 (0.069) **	0.072 (0.078)
RH: High education	0.238 (0.065) ***	0.126 (0.063) **	0.095 (0.067)	0.014 (0.076)
RH: Age > 60	−0.064 (0.084)	−0.035 (0.083)	0.110 (0.088)	0.146 (0.101)
RH: Age < 35	0.397 (0.075) ***	0.268 (0.072) ***	0.292 (0.078) ***	0.242 (0.088) ***
RH: Car owner	0.348 (0.181) *	0.544 (0.178) ***	0.251 (0.184)	0.392 (0.210) *
RH: Male	−0.054 (0.061)	−0.053 (0.060)	0.066 (0.064)	0.063 (0.072)
RH: Have kid under 18	0.571 (0.092) ***	0.559 (0.090) ***	0.387 (0.098) ***	0.484 (0.116) ***
Drive: Income < SG$ 4,000	−0.724 (0.168) ***	−0.708 (0.166) ***	−0.616 (0.190) ***	−0.712 (0.303) **
Drive: Income > SG$ 12,000	0.226 (0.102) **	0.253 (0.099) **	0.172 (0.116)	0.280 (0.182)
Drive: Single	0.343 (0.122) ***	0.328 (0.117) ***	0.334 (0.144) **	0.549 (0.237) **
Drive: Driver license	0.163 (0.112)	0.405 (0.110) ***	0.116 (0.133)	0.098 (0.216)
Drive: Chinese	−0.396 (0.121) ***	−0.456 (0.119) ***	−0.341 (0.139) **	−0.535 (0.227) **
Drive: Commute trip	0.481 (0.094) ***	0.372 (0.092) ***	0.429 (0.109) ***	0.430 (0.174) **
Drive: Full-time job	0.160 (0.096) *	0.051 (0.093)	0.218 (0.111) **	0.238 (0.177)
Drive: High education	−0.047 (0.093)	−0.036 (0.091)	−0.109 (0.107)	−0.198 (0.172)
Drive: Age > 60	−0.244 (0.131) *	−0.351 (0.127) ***	−0.076 (0.155)	−0.179 (0.247)
Drive: Age < 35	−0.178 (0.118)	−0.194 (0.117) *	−0.129 (0.135)	−0.295 (0.219)
Drive: Car owner	0.686 (0.170) ***	0.698 (0.169) ***	0.296 (0.186)	0.530 (0.280) *
Drive: Male	−0.021 (0.093)	−0.126 (0.091)	−0.042 (0.107)	−0.091 (0.169)
Drive: Have kid under 18	0.209 (0.136)	0.147 (0.131)	0.143 (0.158)	0.228 (0.248)
AV: Income < SG$ 4,000	−0.318 (0.083) ***	−0.302 (0.080) ***	−0.217 (0.085) **	−0.226 (0.097) **
AV: Income > SG$ 12,000	0.333 (0.085) ***	0.291 (0.083) ***	0.227 (0.087) ***	0.234 (0.101) **
AV: Single	0.065 (0.088)	0.036 (0.085)	0.080 (0.091)	0.090 (0.104)
AV: Driver license	−0.117 (0.073)	0.038 (0.072)	0.045 (0.076)	0.150 (0.089) *
AV: Chinese	−0.248 (0.079) ***	−0.263 (0.076) ***	−0.055 (0.081)	−0.076 (0.092)
AV: Commute trip	0.369 (0.069) ***	0.326 (0.068) ***	0.211 (0.072) ***	0.230 (0.084) ***
AV: Full-time job	0.237 (0.075) ***	0.122 (0.072) *	0.244 (0.077) ***	0.192 (0.088) **
AV: High education	0.208 (0.072) ***	0.139 (0.070) **	0.076 (0.074)	0.047 (0.084)
AV: Age > 60	0.020 (0.093)	0.018 (0.091)	0.079 (0.097)	0.110 (0.111)
AV: Age < 35	0.482 (0.085) ***	0.335 (0.081) ***	0.360 (0.086) ***	0.317 (0.099) ***
AV: Car owner	−0.053 (0.203)	0.153 (0.199)	−0.141 (0.204)	−0.008 (0.233)
AV: Male	0.127 (0.068) *	0.115 (0.065) *	0.241 (0.070) ***	0.258 (0.081) ***
AV: Have kid under 18	0.325 (0.100) ***	0.310 (0.097) ***	0.099 (0.104)	0.153 (0.119)
Others				
SP scale[3] (μ_{SP})	1.190 (0.056) ***	1.260 (0.057) ***	1.240 (0.070) ***	1.120 (0.091) ***
Walk: HFP[4] (γ_k)	–	–	0.463 (0.055) ***	0.435 (0.061) ***

(*continued on next page*)

Table B1 (*continued*)

Parameter	M1 Base	M2 Base + subjective evaluations	M3 Base + inertia	M4 Base + subjective evaluations + inertia
PT: HFP (γ_k)	–	–	0.234 (0.044) ***	0.254 (0.043) ***
RH: HFP (γ_k)	–	–	0.396 (0.098) ***	0.447 (0.102) ***
Drive: HFP (γ_k)	–	–	0.539 (0.086) ***	0.590 (0.073) ***
PT: Std. Dev. [5] (σ_j)	–	0.019 (0.100)	–	0.939 (0.253) ***
RH: Std. Dev. (σ_j)	–	0.013 (0.143)	–	0.011 (0.123)
Drive: Std. Dev. (σ_j)	–	0.020 (0.171)	–	1.870 (0.433) ***
AV: Std. Dev. (σ_j)	–	0.016 (0.082)	–	0.005 (0.091)
Statistical summary				
Final log-likelihood	−12573.51	−12249.88	−10650.53	−10510.63
AIC	25289.02	24667.76	21485.05	21231.26
BIC	25811.57	25285.99	22162.16	22004.05
ρ^2	0.272	0.291	0.384	0.392
Adjusted ρ^2	0.268	0.286	0.378	0.386

*: p-value < 0.10; **: p-value < 0.05; ***: p-value < 0.01;
5: “Std. Dev.” means standard deviation.
For all models, results were estimated from a sample of 2,003 individuals, 11,613 choice observations, with an initial log-likelihood of −17279.16.
[1] : “Income” means household monthly income.
[2] : “High education” means with Bachelor’s degree or higher.
[3] : The p-value for μ_{SP} is tested against 1 instead of 0 (using *t*-test) because μ_{RP} is normalized to 1. μ_{SP} in all models are>1, meaning RP responses contain more random noise than SP responses (Polydoropoulou and Ben-Akiva, 2001).
[4] : “HFP” means hazard function parameter.

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