

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

3
4 Baichuan Mo
5 Research Assistant
6 Department of Civil and Environmental Engineering
7 Massachusetts Institute of Technology
8 Address: 77 Massachusetts Ave, Cambridge, MA 02139
9 Phone: +1-857-999-5906
10 Email: baichuan@mit.edu

11
12 Qing Yi Wang
13 Research Assistant
14 Department of Civil and Environmental Engineering
15 Massachusetts Institute of Technology
16 Address: 77 Massachusetts Ave, Cambridge, MA 02139
17 Phone: +1-617-890-6979
18 Email: qingyiw@mit.edu

19
20 Joanna Moody, PhD ****corresponding author**
21 Research Program Manager, Mobility Systems Center
22 MIT Energy Initiative
23 Address: 77 Massachusetts Ave, E19-370B, Cambridge, MA 02139
24 Phone: +1-434-409-5679
25 Email: jcmoody@mit.edu

26
27 Yu Shen, PhD
28 Assistant Professor
29 Key Laboratory of Road and Traffic Engineering of the Ministry of Education
30 Tongji University
31 Address: 4800 Cao An Hwy, Jiading, Shanghai, China 201804
32 Phone: +86-21-69589487
33 Email: yshen@tongji.edu.cn

34
35 Jinhua Zhao, PhD
36 Associate Professor
37 Department of Urban Studies and Planning
38 Massachusetts Institute of Technology
39 Address: 77 Massachusetts Ave, 9-523, Cambridge, MA 02139
40 Phone: +1-617-324-7594
41 Email: jinhua@mit.edu

42

1 **Impacts of subjective evaluations and inertia from existing travel modes on**
2 **adoption of autonomous mobility-on-demand**
3
4

5 **HIGHLIGHTS**

- 6 • Model how subjective evaluation of existing modes influence autonomous mobility-on-
7 demand (AMOD) adoption
8 • Model impact of inertia from existing travel modes on AMOD choice
9 • Find that subjective evaluations and inertia both predict mode choice
10 • Particularly, positive evaluations and current use of ridehailing are strongly predictive of
11 AMOD choice
12
13

14 **ABSTRACT**

15 As autonomous vehicle (AV) technology advances, it is important to understand its potential
16 demand and user characteristics. Literature from stated preference surveys find that attitudes and
17 current travel behavior are as or more important than demographics in determining intention to
18 purchase or use AVs. Yet to date no study has looked at how attitudes and use of existing modes
19 both simultaneously affect AV adoption. In this study, we conduct a stated preference survey in
20 Singapore to investigate how the subjective evaluation of existing travel modes (attitudes) and
21 inertia based on previous use of existing modes affect the adoption of an autonomous mobility-on-
22 demand service (AMOD). Using a sample size of 2,003 individuals and 11,613 choice
23 observations, we estimate a mixed logit discrete choice model incorporating latent variables
24 capturing subjective evaluations of existing travel modes (determined through confirmatory factor
25 analysis), a two-part formulation of modal inertia, and other trip-specific and socio-demographic
26 variables. Results show that subjective evaluation and use of existing modes both affect the
27 adoption of AMOD. Specifically, people with a positive evaluation of ridehailing and those who
28 are current ridehailing users are more likely to choose AMOD. Additionally, those who are current
29 car drivers are more likely to choose AMOD, while users of public transit were less likely to choose
30 AMOD. Given that ridehailing is the closest existing mode to our hypothetical AMOD service,
31 our results might suggest that how AVs are implemented and their similarity to existing modes
32 may be critical to the formation of attitudes and direction of inertia impacting adoption. Our
33 research provides insights on the potential relationship between AVs and existing modes that could
34 valuable in AV network design and service planning.
35
36

37 **Keywords:** Autonomous vehicles; mode choice; mixed logit model; factor analysis; latent
38 variables; inertia
39

1. INTRODUCTION

As autonomous vehicle (AV) technology continues to advance, it is important to understand how it will impact our existing 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 (LTA) has announced to pilot and deploy (Bhunja, 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.

1 **2. LITERATURE REVIEW**

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

9
10 Existing research has found that, similar to traditional mode choice, trip characteristics like travel
11 time and travel cost as well as attributes of the built environment are critical predictors of AV
12 adoption (Gkartzonikas and Gkritza, 2019; Nodjomian and Kockelman, 2019; Shabanpour et al.,
13 2018; Becker and Axhausen, 2017; Bansal et al., 2016; Krueger et al., 2016; Yap et al., 2016).
14 Other studies show that socio-demographic characteristics of the traveler also help determine AV
15 adoption decisions. For example, multiple studies have found that younger and more wealthy
16 people have higher interests in and willingness to adopt AVs (Spurlock et al., 2019; Shabanpour
17 et al., 2018; Bansal et al., 2016; Krueger et al., 2016). While the role that gender plays is less
18 certain (Cai et al., 2019; Spurlock et al., 2019; Bansal et al., 2016). Another group of studies have
19 demonstrated that an individual’s previous travel experiences, particularly of car crashes, are
20 correlated with greater interest in AVs and their potential safety benefits (Shabanpour et al., 2018;
21 Bansal et al., 2016).

22 **2.1 General Attitudes and Perceptions of Autonomous Vehicles**

23 Some studies have explored the critical influence of attitudinal factors on people’s stated intention
24 to adopt AVs. One subset of this literature explores how general attitudes towards risk (Wang and
25 Zhao, 2019), innovation and interest in new technologies (Lavieri and Bhat, 2018; Haboucha, et
26 al., 2017), and environmental concerns (Haboucha, et al., 2017; Yap, et al., 2016) affect intention
27 to adopt AVs. Others have considered the influence of perceptions of AV technology, including
28 benefits and performance (Liu, et al., 2019; Hewitt, et al., 2019; Madigan, et al., 2016; Payre 2014;
29 Fraedrich and Lenz 2014; Schoettle and Sivak 2014), safety and trust (Liu, et al., 2019; Yap, et al.,
30 2016; Bansal 2016; Kyriakidis 2015; Payre 2014; Fraedrich and Lenz 2014; Howard and Dai 2014),
31 and hedonic enjoyment (Payre, 2014).

32 **2.2 Existing Travel Behavior**

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

39 **2.3 Our Contribution**

40 While the above studies have explored many of the factors that traditionally influence mode choice,
41 few of them explicitly account for the fact that AMOD would be introduced into an urban mobility
42 system in which there are incumbent modes and established travel patterns. In such situations, both
43 attitudes and actual use of existing transportation modes may influence consumer adoption of AV

1 technology. While previous studies have considered the impact of attitudes towards AV
2 technology on adoption, none have incorporated attitudes towards or perceptions of incumbent
3 travel modes. Furthermore, while some studies have considered how adoption differs among users
4 of cars, transit, and other modes or the influence of travel habits, these studies have not explicitly
5 modeled how the inertia of existing travel behavior might influence AV choice.

6
7 In this study, we add to existing literature by considering how both subjective evaluations and
8 actual use of existing travel modes impact adoption of AMOD over other modes of travel. Research
9 in psychology has firmly established that people’s attitudes and actual behaviors are distinct (e.g.,
10 Ajzen and Fishbein, 1977) and can even be at odds if choices are constrained (e.g., de Vos, 2018
11 for a transportation application and Festinger, 1962 for a general theory of cognitive dissonance).
12 Therefore, we hypothesize that subjective evaluations (attitudes) and inertia are distinct factors
13 that both influence whether an individual will switch from their current travel behavior and adopt
14 a new AMOD service. We incorporate these two concepts into a state-of-the-art hybrid choice
15 model that includes trip characteristics and traveler characteristics and allows for heterogeneity in
16 estimated sensitivities to these explanatory variables (McFadden and Train, 2000). We use
17 confirmatory factor analysis to estimate latent variables representing subjective evaluations of
18 existing travel modes and add them to the model. We incorporate existing use of travel modes as
19 measures of inertia (Cherchi et al., 2017; Cherchi and Manca, 2011; Train, 2009; Yáñez, 2009;
20 Cantillo, et al., 2007). This approach enables us to study the potential substitution patterns of
21 AMOD with other travel modes which can help identify potential user groups of AMOD and draw
22 insights on AV system design.

23 **3. SURVEY DESIGN AND DATA**

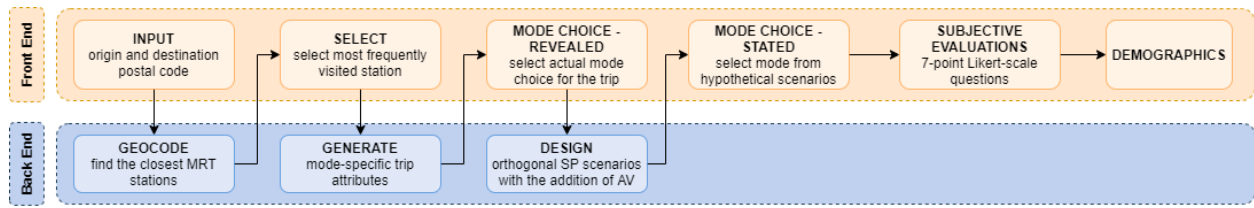
24 This study incorporates people’s subjective evaluations and inertia into the analysis of potential
25 adoption of AMOD services, using data collected from a dynamic online survey administered in
26 Singapore in July 2017 (Shen et al., 2019). Here we present the details on the survey design,
27 introduce the key variables used in the study, and discuss the representativeness of our sample of
28 2,003 individuals and 11,613 choice observations.

29 **3.1 Survey Design**

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

35
36 In the RP portion of the survey, each respondent was first presented with a trip purpose—commute
37 (to work or school), shopping (to grocery store or supermarket), or recreation/entertainment. The
38 respondents were then asked to report the postal codes of trip origin (O) and destination (D), and
39 the mode with which the trip was usually made. Based on the respondent’s revealed OD, some
40 attributes, including walking time, bus access walking time, bus in-vehicle time, ridehailing in-
41 vehicle time, and ridehailing travel cost, were trip-specific and obtained from Google API. Other
42 attributes, including bus travel cost, bus waiting time, and ridehailing waiting time, were static and
43 taken to be the market average.

1 **Figure 1. Survey process diagram**



2
3
4 For the SP portion of the survey, the respondents were asked to choose among incumbent modes
5 (bus, walk, drive, and ridehailing) and a new AMOD service (ridehailing with AV) for the same
6 trip purpose as RP but with varying levels of trip attributes. AMOD was chosen for the study since
7 this was the main form of AV deployment being piloted in Singapore at the time of data collection
8 (Bhunia, 2017). To make sure all respondents were aware of the new technology being presented,
9 every respondent watched an introductory video before answering the SP questions.
















10 **Table 1. SP attribute generation by mode**

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

11
12 Similar to the RP portion, there were static and trip-specific attributes in the SP choice experiment.
13 The static attributes had three levels, with the median anchored to the market average and the
14 high/low values set to the levels specified in Table 1. Each trip-specific attribute also had three
15 levels, with the median anchored to the value calculated from the RP responses, to make the
16 choices were more realistic and familiar to the respondents. High/low values were set as 1.5 and
17 0.5 times the value given in the RP responses, respectively. For the AMOD service (not present in
18 RP), trip-specific attributes were assumed to be similar to those of ridehailing and prices were
19 determined according to the pricing schemes of Uber/Grab at the time in Singapore (Shen et al.,
20 2019; Mo et al., 2021). Given these attributes level, a partial orthogonal balanced design was
21 generated, resulting in 27 scenarios. Six out of these 27 SP scenarios were randomly chosen for
22 each respondent to answer sequentially. While this random blocking destroys the perfect
23 orthogonality of the research design, it is a typical question generation procedure used in AV
24 choice experiments to limit the number of complex questions answered per respondent (e.g.,

1 Haboucha, Ishaq, and Shiftan, 2017; Krueger, Rashidi, and Rose, 2016). A sample interface seen
 2 by respondents is shown in Figure 2.

3 **Figure 2. Example interface for stated preference choice experiment**

		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. Public Transit		\$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

4
 5
 6 The third part of the survey included Likert-scale questions on the subjective evaluation of existing
 7 travel modes. Based on studies by Kroesen et al. (2017) and Molin et al. (2016), we selected five
 8 key attributes of the current travel modes to make up the subjective evaluation: reliability, ease to
 9 use, safety, comfort, and enjoyment. The specific statements are shown in Table 2. For each
 10 statement, responses were collected on a 7-point Likert scale, ranging from “totally disagree” (1)
 11 to “totally agree” (7).

12 **Table 2. Indicators used to derive latent variable measures of subjective evaluation of**
 13 **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.

14

1 **3.2 Sample Socio-demographics and Representativeness**

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

8
 9 Because there are clear differences between the sample and the population in certain demographic
 10 categories, we calculate survey weights using iterative proportional fitting (IPF or raking). Weights
 11 were calculated using the *anesrake* package in R (Pasek, 2018), which implements the American
 12 National Election Study (ANES) weighting algorithm documented in (DeBell and Krosnick, 2009).
 13 Convergence was reached so that weighted sample proportions exactly match the population
 14 proportions for all characteristics listed in Table 3.

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

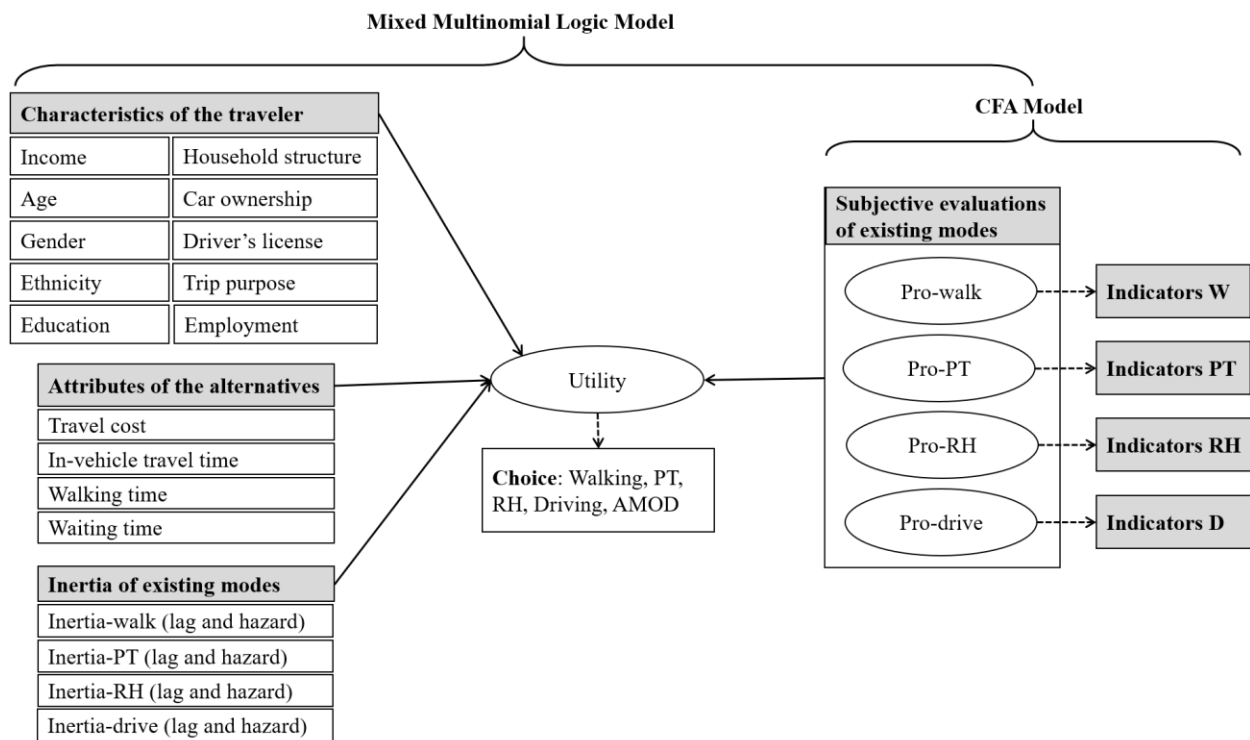
Socio-demographic characteristics	Bin	Sample (%)	Population (%)
Age (as percent of adult population aged 20 or older, 2017)	20-29	29.1	17.5
	30-39	24.6	18.5
	40-49	23.4	19.6
	50-59	15.5	19.6
	60 and older	7.4	24.8
Gender (2017)	Male	45.8	49.0
	Female	54.1	51.0
Ethnicity (2017)	Chinese	85.0	74.3
	Malay	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

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

4 **4. MODEL SPECIFICATION**

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

14 **Figure 3. Path diagram of the hybrid choice model**



15 *Figure note:* Rectangular boxes represent observed variables such as characteristics of respondents and attributes of
 16 choice alternatives (modes), inertia variables, psychometric indicators, and mode choices are represented by
 17 rectangular boxes; ovals represent latent variables such as utilities and subjective evaluations; solid arrows represent
 18 structural equations; dashed arrows represent measurement equations. The CFA model and MMNL model were
 19 estimated sequentially, with factor scores for each subjective evaluation latent variable treated as observed variables
 20 in the choice model.
 21

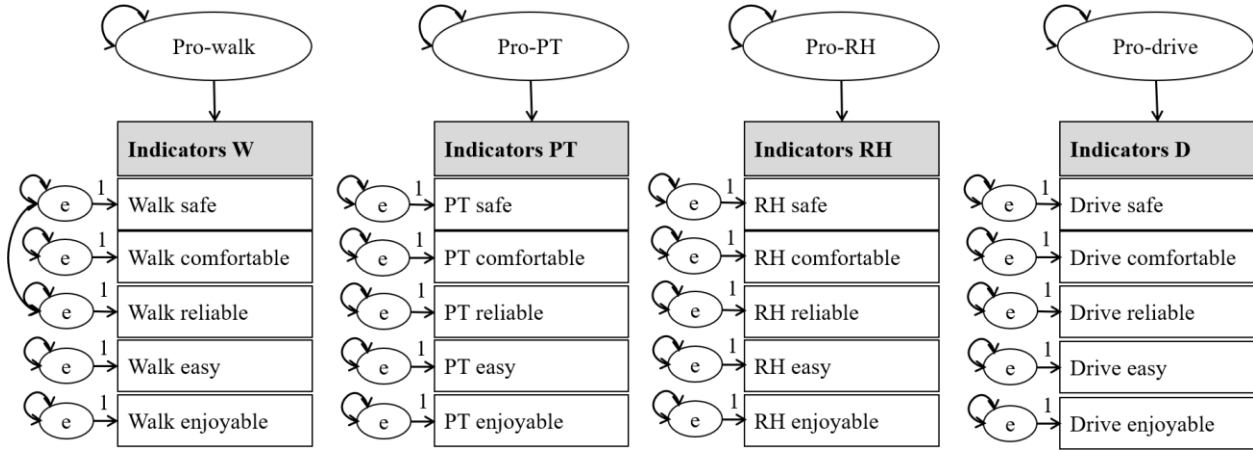
22 **4.1 Subjective Evaluations**

23 Respondent’s subjective evaluations of existing travel modes—walking, public transit (PT),
 24 ridehailing (RH), and driving—are estimated as latent variables based on responses to five

1 indicators related to safety, comfort, reliability, ease of use, and enjoyment of use (see Table 2).
 2 Responses for each indicator were recorded on a 7-point Likert scale, which we treat as ordinal
 3 following best-practice recommendations when including latent factors in hybrid choice models
 4 (Bahamonde-Birke and de Dios Ortúzar, 2017). CFA is used to develop and validate each latent
 5 variable as discussed further in Appendix A.

6
 7 The CFA model structures are shown in Figure 4, with each latent variable validated and estimated
 8 separately. The latent variables represent the subjective evaluations of existing modes, and are
 9 indexed by $m = \{1, 2, 3, 4\}$ that represents pro-walk, pro-PT, pro-RH and pro-drive, respectively.
 10 The indicators were assumed to be independent except for the indicators of safety and reliability
 11 for the pro-walk latent variable based on Lagrange modification indices in the CFA model (see
 12 Appendix A).

14 **Figure 4. Structure of the Confirmatory Factor Analysis models for the subjective**
 15 **evaluation of existing travel modes**



16
 17
 18

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

23
 24 Z_{nmk} takes values on a 7-point Likert scale, and is therefore an ordinal variable. However, the
 25 typical CFA model requires the dependent variable to be continuous. A conventional way to model
 26 ordinal responses in CFA is assuming that there is an underlying unobserved continuous variable
 27 $Z_{nmk}^* \in (-\infty, +\infty)$ that drives the ordered responses Z_{nmk} (Yang-Wallentin et al., 2010; Muthén,
 28 1984). The measurement equation of Z_{nmk}^* is assumed to have the following form:

29
 30 **Eq. (1)**
$$Z_{nmk}^* = \theta_{0mk} + \theta_{1mk}A_{nm} + \eta_{mk}$$

31
 32 where θ_{0mk} is the intercept; θ_{1mk} is the factor loading of the m -th latent variable onto indicator k ;
 33 and $\eta_{mk} \sim \mathcal{N}(0, \sigma_{mk})$ is a normally distributed error term for the m -th latent variable. Note that

1 η_{mk} ($\forall k \in Q_m$) are assumed to be independent unless correlations are introduced explicitly into
 2 the model.

3
 4 The relationship of Z_{nmk} and Z_{nmk}^* can be expressed as

5
 6 **Eq. (2)** $Z_{nmk} = c \Leftrightarrow \tau_{m,c-1} < Z_{nmk}^* < \tau_{m,c}$

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

11
 12 **Eq. (3)**

13
$$\Pr(Z_{nmk} = c | A_{nm}) = \Pr(\tau_{m,c-1} < Z_{nmk}^* < \tau_{m,c} | A_{nm}) = \int_{\tau_{m,c-1} - \theta_{0mk} - \theta_{1mk} A_{nm}}^{\tau_{m,c} - \theta_{0mk} - \theta_{1mk} A_{nm}} \phi_{mk}(\eta) d\eta$$

14
 15 where $\phi_{mk}(\cdot)$ is the probability density function of η_{mk} .

16
 17 To obtain the factor scores for each latent variable for each individual (\hat{A}_{nm}), the expected a
 18 posteriori (EAP) method is used (Estabrook and Neale, 2013; Shi and Lee, 1997). Specifically,

19
 20 **Eq. (4)**
$$\hat{A}_{nm} = E[A_{nm}] = \int_w w f_{A_{nm}|Z}(w) dw = \int_w w \frac{f_{A_{nm}}(w) \Pr(Z | A_{nm}=w)}{\int_{w'} f_{A_{nm}}(w') \Pr(Z | A_{nm}=w') dw'} dw$$

21
 22 where $E[\cdot]$ is the expectation. $f_{A_{nm}|Z}(\cdot)$ is the posteriori probability density function of A_{nm} . \mathbf{Z} is
 23 the vector of all Z_{nmk} . $\Pr(\mathbf{Z} | A_{nm} = w)$ can be calculated as the product of all $\Pr(Z_{nmk} | A_{nm} =$
 24 $w)$. $f_{A_{nm}}(\cdot)$ is the prior probability density function of A_{nm} . Eq. 4 indicates that $A_{nm} = \hat{A}_{nm} +$
 25 δ_m , where δ_m is an error term with mean of zero. In this study, we assume $\delta_m \sim \mathcal{N}(0, \sigma_m^2)$ for the
 26 convenience of the MMNL model estimation.

27 4.2 Inertia of Existing Travel Modes

28 An individual's previous experience may impact their current choice (often termed "inertia").
 29 When individuals are faced with new situations, inertia represents the tendency to stick with past
 30 choices rather than the disposition to change (Train, 2009; Yáñez, 2009; Cantillo et al., 2007). In
 31 this study, we hypothesize that the current use of travel modes poses an inertial effect in the
 32 respondents' stated preferences. The definition of inertia was adapted from Cherchi et al. (2017)
 33 in which inertia was formulated considering both lagged and hazard effects¹, accounting for inertia
 34 from the previous use of existing modes and from repeated selection of an existing mode in the
 35 survey.

36
 37 The sequence of each question is labeled as choice situation t , where $t = 0$ for the RP question
 38 and $t = \{1, \dots, 6\}$ for the SP questions. The lagged inertia of mode j for individual n in choice

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.

situation t , denoted as I_{njt}^L , represents the lagged effect of individual n 's previous choice in the RP question on the individual's current choice. Therefore, I_{njt}^L takes the value 1 if the current choice agrees with the previous choice and 0 otherwise. Mathematically,

$$\text{Eq. (5)} \quad I_{njt}^L = \begin{cases} 1, & \text{if } Y_n^{RP} = j \\ 0, & \text{otherwise} \end{cases} \quad \forall j \in S, t \geq 1$$

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

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_{njt}^H represent the hazard inertia of mode j for individual n in choice situation t , and it is assumed to have the inverse Weibull distribution:

$$\text{Eq. (6)} \quad I_{njt}^H = (FRE_{njt})^{1-\gamma_j} \quad \forall j \in S, t \geq 1$$

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.

4.3 Mixed Multinomial Logit Model

To model people's choices, a MMNL was formulated, with the overall model structure shown in Figure 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:

$$\text{Eq. (7)}$$

$$U_{nj}^{RP} = V_{nj}^{RP} + \varepsilon_j^{RP} = \beta_j^{ASC} + \beta_j^T T_{nj}^{RP} + \beta_j^X X_n + \sum_{m=1}^4 \beta_{mj}^A (\hat{A}_{nm} + \delta_m) + \varepsilon_j^{RP}$$

$$\text{Eq. (8)}$$

$$\begin{aligned}
U_{njt}^{SP} &= V_{njt}^{SP} + \varepsilon_j^{SP} \\
&= \beta_j^{ASC} + \beta_j^T \mathbf{T}_{njt} + \beta_j^X \mathbf{X}_n + \sum_{m=1}^4 \beta_{mj}^A (\hat{A}_{nm} + \delta_m) + \sum_{j' \in S} \beta_{j'j}^L I_{nj't}^L \\
&+ \sum_{j' \in S} \beta_{j'j}^H I_{nj't}^H + \varepsilon_{jt}^{SP}
\end{aligned}$$

where U_{njt}^{SP} and U_{nj}^{RP} 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_j^{ASC} are the alternative-specific constants; \mathbf{T}_{nj}^{RP} and \mathbf{T}_{njt} are alternative-specific trip attributes of mode j ; \mathbf{X}_n is the vector of socio-demographic variables of individual n ; β_j^X , β_j^T , β_{mj}^A , $\beta_{j'j}^L$, and $\beta_{j'j}^H$ are the coefficients to be estimated; ε_j^{RP} and ε_{jt}^{SP} 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 $\tilde{\delta}_j = \sum_{m=1}^4 \beta_{mj}^A \delta_m$ represent the aggregated normal error term with distribution $\mathcal{N}(0, \tilde{\sigma}_j^2 = \sum_{m=1}^4 (\beta_{mj}^A \sigma_m)^2)$. Note that $\tilde{\delta}_j$ 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:

Eq. (9)

$$\Pr(Y_{nt} = j) = \int \Pr(Y_{nt} = j \mid \tilde{\delta}_j = w) \phi_{\tilde{\delta}_j}(w) dw = \int \frac{\exp(\mu V_{njt})}{\sum_{j'' \in C_n} \exp(\mu V_{nj''t})} \phi_{\tilde{\delta}_j}(w) dw$$

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

4.4 Model Estimation

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

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

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

9
10 The estimation procedure consists of two steps: 1) estimating CFA model and output latent factor
11 scores and 2) estimating the MMNL model to get the parameters of interest. In the first step, we
12 fit the ordinal CFA model shown in Figure 4 using diagonally weighted least squares (DWLS)
13 estimation (Li, 2016; Muthén, 1984), a method specifically designed for CFA estimation with
14 ordinal data, as implemented in the R *lavaan* package (Rosseel, 2012). The method makes no
15 distributional assumptions about the observed ordinal variables, and a normal latent distribution
16 underlying each observed ordinal variable is instead assumed (as described in Section 4.1). Then
17 the factor scores for each latent variable and each individual (i.e., \hat{A}_{nm}) are estimated using Eq 3.
18 In the second step, we estimate the MMNL with MSL, obtaining $\beta, \tilde{\sigma}_j$ and μ_{SP} . The model is
19 estimated using PandasBiogeme with 2,000 random draws (Bierlaire, 2018). All input code and
20 results are saved at <https://github.com/mbc96325/Mixture-logit-model-for-AV-adoption>.

21
22 The main models estimated in this paper did not include survey weights. This is because logit
23 models provide unbiased model coefficients regardless of sample representativeness, particularly
24 when all socio-demographic characteristics are included as controls (Bahamonde-Birke and
25 Hanappi, 2016; Efthymiou and Antoniou, 2016). The models were additionally estimated with
26 survey weights as a robustness check, which showed that our main findings were not affected by
27 the unrepresentativeness of our sample (see Appendix B).

28 4.5 Evaluation Scenarios

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

- 31
32
- 33 • M1 (base): Socioeconomic variables + mode attributes
 - 34 • M2 (only subjective evaluations): Socioeconomic variables + mode attributes + subjective
35 evaluations
 - 36 • M3 (only inertia): Socioeconomic variables + mode attributes + inertia
 - 37 • M4 (subjective evaluations + inertia): Socioeconomic variables + mode attributes +
38 subjective evaluations + inertia

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

1 **5. RESULTS AND DISCUSSION**

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

6 **5.1 Correlation between Subjective Evaluation and Inertia**

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

12
13 To verify that our measures of subjective evaluation and inertia are distinct variables, we first
14 consider the correlation matrix between them (Table 4). It shows that almost no correlation exists
15 between subjective evaluations and lag inertia (observed choices) for all modes. Slightly higher
16 correlation exists between subjective evaluations and the hazard inertia (stated preference), but the
17 maximum correlation was 0.411 (for driving).

18
19 To verify that the correlations will not affect model estimation, the variance inflation factors (VIFs)
20 were estimated (Table 4). The variance inflation factor is a standard measure of multicollinearity,
21 which is the inverse of the R² value of the linear regression between the target variable and all
22 other variables. A high VIF means that the target variable can be expressed as a linear combination
23 of all other variables with a strong fit; therefore, multicollinearity problems will follow if all
24 variables are included in model estimation. The common rule of thumb is that a value higher than
25 5 or 10 indicates severe multicollinearity that needs to be addressed (O’Brien 2007). In this case,
26 the highest VIF score is 3.35, which means that no significant multicollinearity problems exist in
27 including both the subjective evaluations and the inertia terms in the choice model. Therefore, we
28 conclude that our measure of subjective evaluations, observed use of existing modes (lag-inertia),
29 and repeated stated preference for a mode (hazard-inertia) can all play different roles in people’s
30 mode choice.

31 **Table 4. Pearson correlation coefficients (ρ) between and VIF of subjective evaluation and**
32 **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

33 **5.2 Model Fit**

34 To evaluate model fit, four metrics were calculated: log-likelihood, Akaike Information Criterion
35 (AIC), Bayesian Information Criterion (BIC), and adjusted ρ². The values are presented in the
36 bottom panel of Table 5. For all metrics, model performances improved from M1 to M4, meaning
37 both subjective evaluations and inertia improved the explanatory power of the model. Among the

1 improvements, M3 and M4 were significantly better than M1 and M2. Although both helped to
 2 improve the model fit, the actual choices (represented by inertia) can better model people's stated
 3 preferences than their subjective evaluations of the alternatives. Nevertheless, M4 was better than
 4 M3 along all dimensions; therefore, subjective evaluations did play a role in the respondents' stated
 5 preferences. Further, the parameters estimated for the explanatory variables (subjective
 6 evaluations, inertia, sociodemographic variables, and except for alternative-specific constants) had
 7 the same sign and similar magnitudes in all models. Therefore, the results from M4 in which all
 8 factors were included are discussed in the following sections.

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

Parameter	M1 Base	M2 Base + subjective evaluations	M3 Base + inertia	M4 Base + subjective evaluations + inertia
<i>Alternative specific constants (β^{ASC})</i>				
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) **
<i>Subjective evaluations (β_m^A)</i>				
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)
<i>Inertia (lagged β_j^I and hazard β_j^H)</i>				
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) **
<i>Mode attributes (β_T)</i>				
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) ***

Parameter	M1 Base	M2 Base + subjective evaluations	M3 Base + inertia	M4 Base + subjective evaluations + inertia
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)
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) ***

Parameter	M1 Base	M2 Base + subjective evaluations	M3 Base + inertia	M4 Base + subjective evaluations + inertia
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 ($\tilde{\sigma}_j$)	-	0.486 (0.138) ***	-	1.390 (0.209) ***
RH: Std. Dev. ($\tilde{\sigma}_j$)	-	0.003 (0.136)	-	0.010 (0.123)
Drive: Std. Dev. ($\tilde{\sigma}_j$)	-	0.009 (0.109)	-	1.770 (0.310) ***
AV: Std. Dev. ($\tilde{\sigma}_j$)	-	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;

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 greater than 1, meaning RP responses contain more random noise than SP responses (Polydoropoulou and Ben-Akiva, 2001).

4: "HFP" means hazard function parameter.

5: "Std. Dev." means standard deviation.

1 Table notes: For all models, results were estimated from a sample of 2,003 individuals, 11,613 choice observations,
2 with an initial log-likelihood of -16764.55.

3 5.3 Inertia

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

9
10 We start with a discussion of the lagged inertia variables. For existing modes, greater familiarity
11 from use of the existing mode did not always lead to a greater likelihood of choosing it in the
12 hypothetical choice scenarios. For ridehailing (and, not significantly, driving), the coefficient for
13 lagged inertia is positive, suggesting that the users of these current modes were more likely to
14 continue using them. In other words, respondents that are currently using car-based modes are
15 doing so by choice. On the other hand, the choices to walk or take public transit were negatively
16 predicted by existing use of those modes. Individuals who were walking and taking public transit
17 tended to switch modes if a better alternative was presented in their stated preference choice sets.
18 This result might suggest that individuals currently walk or take public transit in Singapore because
19 they lacked an affordable or easy alternative rather than because it is their true preference.

20
21 Considering likelihood to switch to AMOD from existing modes, we found that users with greater
22 lag inertia for ridehailing were the most likely to switch to AMOD, followed by driving, public
23 transit, and then walking. All else being equal, individuals who currently use ridehailing and drive

1 their personal car were the most likely to switch to AMOD when it becomes available, with
2 coefficients of lag inertia of 1.600 and 0.702, respectively. This could indicate that individuals are
3 more likely to adopt a new AMOD when it is similar to what they already use to travel—e.g.,
4 ridehailing, or to a lesser extent, driving a car. Cai et al. (2019) reached similar conclusions by
5 estimating AV choice models separately for Singaporean drivers and transit users.

6
7 All hazard inertia coefficients for the existing modes are statistically significant and positive,
8 meaning that people tend to choose one mode repeatedly when presented with different choice
9 scenarios. This may be reflective of an anchoring effect where people are overly reliant on the first
10 piece of information for decision-making and evaluate latter scenarios with respect to the previous
11 ones. In other words, respondents may have related subsequent choice scenarios to a previous one,
12 deciding whether to switch from the previous choice. For the choice of switching to AMOD we
13 again find an effect similar to lagged inertia, where people who previously chose ridehailing in the
14 choice experiments were the most likely to switch to AMOD in subsequent choice scenarios. The
15 coefficient for hazard inertia is strongly positive for ridehailing and negative for walking. **The
16 hazard inertia terms for both driving and public transit were not consistently statistically different
17 from zero across the weighted and unweighted models (see Appendix B).**

18 **5.4 Subjective Evaluations of Existing Travel Modes (Attitudes)**

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

26
27 In general, we find that positive evaluations of an existing mode contribute to a greater likelihood
28 of choosing that mode. For example, those who had stronger positive evaluations of walking,
29 public transit, ridehailing, and driving were more likely to choose these modes. Subjective
30 evaluations of existing modes are less predictive of stated preference towards a new travel mode,
31 in our case AMOD. **M4 finds that an individual’s subjective evaluations of driving and public
32 transit do not significantly influence choice to use AMOD, while having a positive attitude towards
33 ridehailing and walking is a significant predictor of choosing AMOD (see also weighted model
34 results in Appendix B).** Since ridehailing, being a chauffeured mobility-on-demand service, is the
35 most similar to our hypothetical AMOD mode in terms of its trip attributes, this finding might
36 suggest that positive evaluations of existing services that were similar to in terms of service design
37 may help to predict adoption of new technologies. However, this positive relationship between
38 ridehailing attitudes and AMOD choice may alternatively be due to other shared predictors not
39 captured in the model, such as an individual’s familiarity with smartphone apps, propensity or
40 interest in using new technologies in general, or other factors.

41
42 Since subjective evaluations matter in decision making and it is difficult to ask for people’s
43 evaluations on something not implemented, close neighbors to new technologies might be used as
44 proxies to evaluate people’s likely reactions towards and identify potential adopters of new
45 transportation modes or technologies. But the choice of proxy is not a trivial issue; it depends not

1 only on the technology itself, but also on how the technology will be implemented within the
2 mobility system.

3 **5.5 Socio-demographic Variables and Mode Attributes**

4 Finally, we briefly discuss the estimated parameters for the socio-demographic characteristics of
5 travelers (β_X) and mode attributes (β_T) for M4 shown in Table 5.

6 *5.5.1 Mode-Specific Attributes*

7 When it comes to mode-specific attributes, we find that all travel time and cost related variables
8 have negative coefficients, as expected, and are statistically different from zero with p-value < .01.
9 We can also use these coefficients to estimate values of in-vehicle, waiting, and walking time for
10 our different mode choices (Table 6).

11
12 Comparing the cost and in-vehicle time coefficients across modes, we find that individuals are the
13 most sensitive to PT travel cost and least sensitive to PT travel time—suggesting that people take
14 public transport with the expectation that it is not time-efficient. From the estimated coefficients
15 for AMOD, we see that individuals are expecting this service to be time-efficient. We also find
16 that the choice to take AMOD or ridehailing is more sensitive to waiting time than public transit.
17 Finally, we find that the value of walking time for driving is similar in magnitude to the value of
18 waiting time for both AMOD and ridehailing.

19 **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	--

20

21 *5.5.2 Characteristics of Travelers*

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

28

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

1 but not significant indicator of AMOD adoption after controlling for subjective evaluation and use
2 of existing modes.

3
4 When it comes to age, gender, and ethnicity, we find that younger people have a greater inclination
5 towards ridehailing and AMOD (in line with Cai et al., 2019; Liu et al., 2019; Shabanpour et al.,
6 2018) as well as driving. Gender is not found to be a significant predictor of mode choice, whereas
7 people who self-report as Chinese ethnicity are less likely to take ridehailing and AMOD.

8
9 As expected, we find that people with a driver's license are more likely to drive than walk and less
10 likely to take ridehailing or public transit. It is not a significant predictor of AMOD choice.
11 Relatedly, having more cars in the household predicts greater choice of driving and ridehailing.
12 The finding that car ownership is positively predictive of ridehailing adoption has been observed
13 in other survey studies in Singapore (Moody and Zhao, 2020) and may reflect the fact that car
14 owners are accustomed to traveling with car-based modes. Car ownership, like having a driver's
15 license, is not significantly predictive of AMOD choice.

16
17 Finally, when it comes to trip purpose, we find that all modes are preferred over walking for
18 commuting trips, with the most preferred mode being public transport.

19 **6. CONCLUSION**

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

31
32 We found that subjective evaluations and past mode use are related, but distinct constructs that
33 jointly influence people's future mode choices. In general, we found that individuals who have
34 positive subjective evaluations of a given mode are more likely to choose it for their trip and that,
35 even controlling for these attitudes and other individual- and mode-specific attributes, there is
36 indeed significant inertia in mode choice.

37
38 When it comes to modeling the adoption of a new, hypothetical AMOD service, we find that
39 individuals with positive attitudes towards and existing use of car-based modes that are similar to
40 the new AV service are more likely to switch to AMOD. In particular, we found that people with
41 a positive evaluation of ridehailing and those that are currently ridehailing users are the most likely
42 to choose AMOD. Additionally, those who are current car drivers are more likely to choose
43 AMOD, while users of public transit were less likely to choose AMOD. Given that ridehailing is
44 the closest existing mode to our hypothetical AMOD service, our results might suggest that how
45 AVs are implemented and their similarity to existing modes may be critical to the formation of

1 attitudes and direction of inertia impacting adoption. However, future work is needed to further
2 explore the substitutability between existing, chauffeured ridehailing services and new AMOD
3 services.

4
5 This finding may have significant implications for how we predict adoption of and design service
6 for AVs. We find that subjective evaluations of existing modes provide useful information only
7 when the proposed implementation is similar enough to an existing mode. When we measure
8 people's acceptance of new technologies, contexts that relate to the individual's perceptions and
9 use of existing travel options can help to solicit meaningful intentions. On the other hand,
10 interactions with existing modes, represented by inertia, provide more information on whether
11 people will choose the newly introduced travel mode. The study found that people familiar with
12 mobility options that are already similar to the newly proposed mode had a greater tendency to
13 switch. Here we caution that the purpose of our model is in describing rather than predicting
14 adoption of AV services. If our model were to be used for prediction, further model calibration
15 and appropriate weighting of the sample to be representative of the Singaporean population would
16 likely be necessary.

17
18 While this work contributes to existing understanding of user adoption of autonomous vehicle
19 technology and extends the state-of-practice on mode choice modeling with latent variables and
20 inertial terms, there remain many areas for future research. For example, our study only considered
21 one form of AV implementation, namely an autonomous mobility-on-demand service. Since we
22 found that both subjective evaluations and inertia from use of existing modes are most influential
23 when the existing mode is very similar to the new mode introduced in the choice experiment, it
24 could be interesting to study these same research questions for other forms of AV deployment,
25 such as private ownership or autonomous public transit. The impact of subjective evaluations and
26 inertia on different AV implementations may corroborate or challenge the interpretation of the
27 model results presented in this study. Furthermore, research could consider how subjective
28 evaluation and current use of existing travel modes influence AV choice in other settings or for
29 specific groups of individuals (perhaps using latent classes), thereby helping to generalize the
30 findings from this study to other geographies or target populations of interest. Finally, as AV
31 technology matures and becomes commercially available in the mobility market, it will be
32 important to observe actual user adoption of these services and compare these revealed preferences
33 with previous stated preference studies.

34 **ACKNOWLEDGEMENT**

35 This study is supported by Natural Science Foundation of Shanghai (19ZR1460700) and the
36 Fundamental Research Funds for the Central Universities (22120180569). The research is also
37 supported by the National Research Foundation, the Prime Minister's Office of Singapore under
38 the CREATE program, and the SMART's Future Urban Mobility IRG. The survey has been
39 approved by MIT's Committee on the Use of Humans as Experimental Subjects under Protocol
40 1609690311.

41 **REFERENCES**

42 Abdullah, Z. 2019. Entire western part of Singapore to become testing ground for driverless
43 vehicles. *Channel News Asia*, October 24.
44 <https://www.channelnewsasia.com/news/singapore/autonomous-vehicles-western->

1 [singapore-testbed-12029878](https://doi.org/10.1016/j.tra.2015.11.002)

- 2 Ajzen, I., and M. Fishbein. 1977. Attitude-behavior relations: A theoretical analysis and review
3 of empirical research. *Psychological Bulletin* 84, 4, 888–918. [https://doi.org/10.1037/0033-](https://doi.org/10.1037/0033-2909.84.5.888)
4 [2909.84.5.888](https://doi.org/10.1037/0033-2909.84.5.888)
- 5 Bahamonde-Birke, F.J., and T. Hanappi. 2016. The potential of electromobility in Austria:
6 Evidence from hybrid choice models under the presence of unreported information.
7 *Transportation Research Part A: Policy and Practice* 83, 30–41.
8 <https://doi.org/10.1016/j.tra.2015.11.002>
- 9 Bahamonde-Birke, F.J., and J. de Dios Ortúzar. 2017. Analyzing the continuity of attitudinal and
10 perceptual indicators in hybrid choice models. *Journal of Choice Modelling* 25, 28–39.
11 <https://doi.org/10.1016/j.jocm.2017.01.003>
- 12 Bansal, P., K.M. Kockelman, and A. Singh. 2016. Assessing public opinions of and interest in
13 new vehicle technologies: An Austin perspective. *Transportation Research Part C:*
14 *Emerging Technologies* 67, 1–14. <https://doi.org/10.1016/j.trc.2016.01.019>
- 15 Basu, R., A. Araldo, A.P. Akkinapally, B.H. Nahmias Biran, K. Basak, R. Seshadri, N.
16 Deshmukh, N. Kumar, C.L. Azevedo, and M. Ben-Akiva. 2018. Automated mobility-on-
17 demand vs. mass transit: A multi-modal activity-driven agent-based simulation approach.
18 *Transportation Research Record* 2672, 608–618.
19 <https://doi.org/10.1177/0361198118758630>
- 20 Becker, F., and K.W. Axhausen. 2017. Literature review on surveys investigating the acceptance
21 of automated vehicles. *Transportation* 44, 1293–1306. [https://doi.org/10.1007/s11116-017-](https://doi.org/10.1007/s11116-017-9808-9)
22 [9808-9](https://doi.org/10.1007/s11116-017-9808-9)
- 23 Ben-Akiva, M., M. Bradley, T. Morikawa, J. Benjamin, T. Novak, H. Oppewal, and V. Rao.
24 1994. Combining revealed and stated preferences data. *Marketing Letters* 5, 335–349.
- 25 Bhunia, P. 2017. Singapore moves ahead on smart mobility – Autonomous scheduled and on-
26 demand public transport by 2022; first AV test centre opened.” *OpenGovAsia*, December
27 22. [https://opengovasia.com/singapore-moves-ahead-on-smart-mobility-autonomous-](https://opengovasia.com/singapore-moves-ahead-on-smart-mobility-autonomous-scheduled-and-on-demand-public-transport-by-2022-first-av-test-centre-opened/)
28 [scheduled-and-on-demand-public-transport-by-2022-first-av-test-centre-opened/](https://opengovasia.com/singapore-moves-ahead-on-smart-mobility-autonomous-scheduled-and-on-demand-public-transport-by-2022-first-av-test-centre-opened/)
- 29 Bierlaire, M. 2018. *PandasBiogeme: a short introduction*. Technical Report. Ecole
30 Polytechnique Fédérale de Lausanne (EPFL). [https://transp-](https://transport.epfl.ch/documents/technicalReports/Bier18.pdf)
31 [or.epfl.ch/documents/technicalReports/Bier18.pdf](https://transport.epfl.ch/documents/technicalReports/Bier18.pdf)
- 32 Cai, Y., H. Wang, G.P. Ong, Q. Meng, and D.H. Lee. 2019. Investigating user perception on
33 autonomous vehicle (AV) based mobility-on-demand (MOD) services in Singapore using
34 the logit kernel approach. *Transportation* 46, 2063–2080. [https://doi.org/10.1007/s11116-](https://doi.org/10.1007/s11116-019-10032-8)
35 [019-10032-8](https://doi.org/10.1007/s11116-019-10032-8)
- 36 Cantillo, V., J. de Dios Ortúzar, and H.C.W.L. Williams. 2007. Modeling discrete choices in the
37 presence of inertia and serial correlation. *Transportation Science* 41, 1, 195–205.
38 <https://doi.org/10.1287/trsc.1060.0178>
- 39 Cherchi, E., T. Rashidi, M. Börjesson, and M. Bierlaire. 2017. Habitual latent behavior and
40 dynamic effect of inertia: Lagged-based versus hazard-based hybrid mode choice model.
41 *Proceedings of the 96th Annual Meeting of the Transportation Research Board*.
42 <https://trid.trb.org/view/1438923>
- 43 DeBell, M, and J. A. Krosnick. 2009. “Computing weights for American National Election Study
44 survey data,” *ANES Technical Report Series*, No. nes012427.
- 45 De Vos, J. 2018. Do people travel with their preferred travel mode? Analysing the extent of
46 travel mode dissonance and its effect on travel satisfaction. *Transportation Research Part*

- 1 A: *Policy and Practice* 117, 261–274. <https://doi.org/10.1016/j.tra.2018.08.034>
- 2 Efthymiou, D., and C. Antoniou. 2016. Modeling the propensity to join carsharing using hybrid
3 choice models and mixed survey data. *Transport Policy* 51, 143–149.
4 <https://doi.org/10.1016/j.tranpol.2016.07.001>
- 5 Estabrook, R., and M. Neale. 2013. A comparison of factor score estimation methods in the
6 presence of missing data: Reliability and an application to nicotine dependence.
7 *Multivariate Behavioral Research* 48, 1–27. <https://doi.org/10.1080/00273171.2012.730072>
- 8 Fagnant, D.J., and K. Kockelman. 2015. Preparing a nation for autonomous vehicles:
9 Opportunities, barriers and policy recommendations. *Transportation Research Part A:*
10 *Policy and Practice* 77, 167–181. <https://doi.org/10.1016/j.tra.2015.04.003>
- 11 Festinger, L. 1962. Cognitive dissonance. *Scientific American* 207, 4, 93–107.
- 12 Fraedrich, E., and B. Lenz. 2014. Automated driving—Individual and societal aspects entering
13 the debate. *Transportation Research Record* 2416, 64–72. <https://doi.org/10.3141/2416-08>
- 14 Gkartzonikas, C., and K. Gkritza. 2019. What have we learned? A review of stated preference
15 and choice studies on autonomous vehicles. *Transportation Research Part C: Emerging*
16 *Technologies* 98, 323–337. <https://doi.org/10.1016/j.trc.2018.12.003>
- 17 Gruel, W., and J.M. Stanford. 2016. Assessing the long-term effects of autonomous vehicles: A
18 speculative approach. *Transportation Research Procedia* 13, 18–29.
19 <https://doi.org/10.1016/j.trpro.2016.05.003>
- 20 Haboucha, C.J., R. Ishaq, and Y. Shiftan. 2017. User preferences regarding autonomous vehicles.
21 *Transportation Research Part C: Emerging Technologies* 78, 37–49.
22 <https://doi.org/10.1016/j.trc.2017.01.010>
- 23 Hewitt, C., T. Amanatidis, I. Politis, and A. Sarkar. 2019. Assessing public perception of self-
24 driving cars: The autonomous vehicle acceptance model. *Proceedings of the 24th*
25 *International Conference on Intelligent User Interfaces*.
- 26 Howard, D., and D. Dai. 2013. Public perceptions of self-driving cars: The case of Berkeley,
27 California. *Proceedings of the 93rd Annual Meeting of the Transportation Research Board*.
28 <https://trid.trb.org/view/1289421>
- 29 Kroesen, M., S. Handy, and C. Chorus. 2017. Do attitudes cause behavior or vice versa? An
30 alternative conceptualization of the attitude-behavior relationship in travel behavior
31 modeling. *Transportation Research Part A: Policy and Practice* 101, 190–202.
32 <https://doi.org/10.1016/j.tra.2017.05.013>
- 33 Krueger, R., T.H. Rashidi, and J.M. Rose. 2016. Preferences for shared autonomous vehicles.
34 *Transportation Research Part C: Emerging Technologies* 69, 343–355.
35 <https://doi.org/10.1016/j.trc.2016.06.015>
- 36 Kyriakidis, M., R. Happee, and J.C.F. de Winter. 2015. Public opinion on automated driving:
37 Results of an international questionnaire among 5000 respondents. *Transportation Research*
38 *Part F. Traffic Psychology and Behavior* 32, 127–140.
39 <https://doi.org/10.1016/j.trf.2015.04.014>
- 40 Lavieri, P., and C. Bhat. 2019. Investigating objective and subjective factors influencing the
41 adoption, frequency, and characteristics of ride-hailing trips. *Transportation Research Part*
42 *C: Emerging Technologies* 105, 100–125. <https://doi.org/10.1016/j.trc.2019.05.037>
- 43 Li, C-H. 2016. Confirmatory factor analysis with ordinal data: Comparing robust maximum
44 likelihood and diagonally weighted least squares. *Behavioral Research Methods* 48, 3, 936–
45 949. <https://doi.org/10.3758/s13428-015-0619-7>
- 46 Liu, P., Q. Guo, F. Ren, L. Wang, and Z. Xu. 2019. Willingness to pay for self-driving vehicles:

1 Influences of demographic and psychological factors. *Transportation Research Part C: Emerging Technologies* 100, 306–317. <https://doi.org/10.1016/j.trc.2019.01.022>

2
3 Madigan, R., T. Louw, M. Dziennus, T. Graindorge, E. Ortega, M. Merat, and N. Graindorge. 2016. Acceptance of automated road transport systems (ARTS): An adaptation of the
4 UTAUT model. *Transportation Research Procedia* 14, 2217–2226.
5 <https://doi.org/10.1016/j.trpro.2016.05.237>

6
7 McFadden D., and K. Train. 2000. Mixed MNL models for discrete response. *Journal of Applied Economics* 15, 447–470.
8

9 Milakis, D., M. Snelder, B. van Arem, B. van Wee, and G.H. de Almeida Correia. 2017. Development and transport implications of automated vehicles in the Netherlands:
10 Scenarios for 2030 and 2050. *European Journal of Transport and Infrastructure Research*
11 17, 63–85. <https://doi.org/10.18757/ejtir.2017.17.1.3180>

12
13 Mo, B., Z. Cao, H. Zhang, Y. Shen, and J. Zhao. 2021. Competition between shared autonomous vehicles and public transit: A case study in Singapore. *Transportation Research Part C: Emerging Technologies* Forthcoming.
14
15

16 Molin, E., P. Mokhtarian, and M. Kroesen. 2016. Multimodal travel groups and attitudes: A latent class cluster analysis of Dutch travelers. *Transportation Research Part A: Policy and Practice* 83, 14–29. <https://doi.org/10.1016/j.tra.2015.11.001>
17
18

19 Moody, J. and J. Zhao. 2020. Adoption of exclusive and pooled TNC services in Singapore and the U.S. *Journal of Transportation Engineering Part A: Systems* 146, 9, 04020102.
20
21 <https://doi.org/10.1061/JTEPBS.0000438>

22 Muthén, B., 1984. A general structural equation model with dichotomous, ordered categorical, and continuous latent variable indicators. *Psychometrika* 49, 115–132.
23

24 Nieuwenhuijsen, J., G.H. de Almeida Correia, D. Milakis, B. van Arem, and E. van Daalen. 2018. Towards a quantitative method to analyze the long-term innovation diffusion of automated vehicles technology using system dynamics. *Transportation Research Part C: Emerging Technologies* 86, 300–327. <https://doi.org/10.1016/j.trc.2017.11.016>
25
26
27

28 Nodjomian, A.T., and K. Kockelman. 2019. How does the built environment affect interest in the ownership and use of self-driving vehicles? *Journal of Transport Geography* 78, 115–134.
29
30 <https://doi.org/10.1016/j.jtrangeo.2019.05.016>

31 O'Brien, R. M. 2007. A caution regarding rules of thumb for variance inflation factors. *Quality & Quantity* 41, 673–690. <https://doi.org/10.1007/s11135-006-9018-6>
32

33 Pasek, J. 2018. Package 'anesrake.' <https://cran.r-project.org/web/packages/anesrake/anesrake.pdf>
34

35 Payre, W., J. Cestac, and P. Delhomme. 2014. Intention to use a fully automated car: Attitudes and a priori acceptability. *Transportation Research Part F: Traffic Psychology and Behaviour* 27, B, 252–263. <https://doi.org/10.1016/j.trf.2014.04.009>
36
37

38 Polydoropoulou, A., and M. Ben-Akiva. 2001. Combined revealed and stated preference nested logit access and mode choice model for multiple mass transit technologies. *Transportation Research Record* 1771, 38–45.
39
40

41 Rosseel, Y. 2012. lavaan: An R Package for Structural Equation Modeling. *Journal of Statistical Software* 48, 2. <https://doi.org/10.18637/jss.v048.i02>
42

43 Shabanpour, R., N. Golshani, A. Shamshiripour, and A. K. Mohammadian. 2018. Eliciting preferences for adoption of fully automated vehicles using best-worst analysis. *Transportation Research Part C: Emerging Technologies* 93, 463–478.
44
45
46 <https://doi.org/10.1016/j.trc.2018.06.014>

- 1 Schoettle, B., and M. Sivak. 2014. *A survey of public opinion about autonomous and self-driving*
2 *vehicles in the U.S., the U.K., and Australia*. Technical Report. University of Michigan
3 Transportation Research Institute. <http://hdl.handle.net/2027.42/108384>
- 4 Shen, Y., B. Mo, X. Zhang, and J. Zhao. 2019. Built environment and autonomous vehicle mode
5 choice: A first-mile scenario in Singapore. *Proceedings of the 98th Annual Meeting of the*
6 *Transportation Research Board*.
- 7 Shi, J-Q. and Lee, S-Y. 1997. A Bayesian estimation of factor score in confirmatory factor model
8 with polytomous, censored, or truncated data. *Psychometrika* 62, 1, 29-50.
9 <https://doi.org/10.1007/BF02294779>
- 10 Singapore Department of Statistics. 2018. *Population Trends, 2017*.
11 <https://www.singstat.gov.sg/-/media/files/publications/population/population2017.pdf>
- 12 Singapore Department of Statistics. 2020. "Table 8. Resident Households by Monthly Household
13 Income from Work, 2010 – 2020)." In *Key Household Income Trends, 2020*.
14 <https://www.singstat.gov.sg/-/media/files/publications/households/pp-s27.pdf>
- 15 Singapore Department of Statistics. 2021. "Household Expenditure Survey 2017/18: Ownership
16 of Consumer Durables (as percent of all resident households)."
17 <https://www.singstat.gov.sg/modules/infographics/hes/ownership-of-consumer-durables>
- 18 Spurlock, C.A., J. Sears, G. Wong-Parodi, V. Walker, L. Jin, M. Taylor, A. Duvall, A. Gopal,
19 and A. Todd. 2019. Describing the users: Understanding adoption of and interest in shared,
20 electrified, and automated transportation in the San Francisco Bay Area. *Transportation*
21 *Research Part D: Transport and Environment* 71, 283–301.
22 <https://doi.org/10.1016/j.trd.2019.01.014>
- 23 Train, K.E., 2009. *Discrete choice methods with simulation*. Cambridge University Press.
- 24 Vij, A., A. Carrel, and J. L. Walker. 2013. Incorporating the influence of latent modal preferences
25 on travel mode choice behavior. *Transportation Research Part A: Policy and Practice* 54,
26 164–178. <https://doi.org/10.1016/j.tra.2013.07.008>
- 27 Wang, S., and J. Zhao. 2019. Risk preference and adoption of autonomous vehicles.
28 *Transportation Research Part A: Policy and Practice* 126, 215–229.
29 <https://doi.org/10.1016/j.tra.2019.06.007>
- 30 Yáñez, M.F. 2009. Inertia and shock effects on mode choice panel data: Implications of the
31 Transantiago implementation. *Proceedings of the 12th International Conference on Travel*
32 *Behaviour Research*.
- 33 Yang-Wallentin, F., K.G. Jöreskog, and H. Luo. 2010. Confirmatory factor analysis of ordinal
34 variables with misspecified models. *Structural Equation Modeling* 17, 9, 392–423.
35 <https://doi.org/10.1080/10705511.2010.489003>
- 36 Yap, M.D., G. Correia, and B. van Arem. 2016. Preferences of travellers for using automated
37 vehicles as last mile public transport of multimodal train trips. *Transportation Research*
38 *Part A: Policy and Practice* 94, 1–16. <https://doi.org/10.1016/j.tra.2016.09.003>
- 39 Zmud, J.P., and I.N. Sener, 2017. Towards an understanding of the travel behavior impact of
40 autonomous vehicles. *Transportation Research Procedia*.
41 <https://doi.org/10.1016/j.trpro.2017.05.281>
42

1 **APPENDIX A: RESULTS OF CONFIRMATORY FACTOR ANALYSIS**

2 **Convergent Validity**

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

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

21 **Table A1. Standardized factor loadings and R^2 values for CFA models (estimated separately for each subjective**
 22 **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
	<i>correlation between errors for safe and reliable</i>	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

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

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

Model	χ^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

2 **Divergent Validity**

3 Having established the convergent validity of our latent variables, we now want to ensure that they
 4 collectively demonstrate reasonable divergent (or discriminant) validity. We run a CFA model
 5 simultaneously estimating the final specifications of all of our latent variables and allowing them
 6 to correlate. We are looking to show that items presumed to measure a certain latent variable do
 7 not have significant cross-loadings with other latent variable. We only estimate this combined CFA
 8 model for the subset of respondents
 9

10 This combined CFA model demonstrates moderately acceptable model fit across multiple indices:
 11 $\chi^2(N = 953, df = 163) = 3966.99, p < .01$, CFI = 0.917, TLI = 0.904, RMSEA = 0.075 with 90%
 12 CI [0.072, 0.078], and SRMR = 0.096. Of particular interest for discriminant validity is the
 13 correlations among the latent variables given in Table A3. We find these correlations range
 14 between 0.288 and 0.737, suggested that they are related, but distinct variables.
 15

16 **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

17 We additionally consider the MIs among the latent variables and their indicators. We find that
 18 there are only a few MIs large enough to suggest potential cross-loading of indicators among latent
 19 variables. However, given the moderate model fit without these cross-loadings, we do not include
 20 them when estimating the correlations above.
 21

22 **Reliability**

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

28 **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

1

2 **APPENDIX B: MODEL ESTIMATION RESULTS WITH SAMPLE WEIGHTS**

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

Parameter	M1 Base	M2 Base + subjective evaluations	M3 Base + inertia	M4 Base + subjective evaluations + inertia
<i>Alternative specific constants (β^{ASC})</i>				
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) ***
<i>Subjective evaluations (β_m^A)</i>				
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)
<i>Inertia (lagged β_j^I and hazard β_j^H)</i>				
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)
<i>Mode attributes (β_r)</i>				
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) ***
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) ***

Parameter	M1 Base	M2 Base + subjective evaluations	M3 Base + inertia	M4 Base + subjective evaluations + inertia
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				

Parameter	M1 Base	M2 Base + subjective evaluations	M3 Base + inertia	M4 Base + subjective evaluations + inertia
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) ***
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 ($\tilde{\sigma}_j$)	-	0.019 (0.100)	-	0.939 (0.253) ***
RH: Std. Dev. ($\tilde{\sigma}_j$)	-	0.013 (0.143)	-	0.011 (0.123)
Drive: Std. Dev. ($\tilde{\sigma}_j$)	-	0.020 (0.171)	-	1.870 (0.433) ***
AV: Std. Dev. ($\tilde{\sigma}_j$)	-	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;

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 greater than 1, meaning RP responses contain more random noise than SP responses (Polydoropoulou and Ben-Akiva, 2001).

⁴: "HFP" means hazard function parameter.

⁵: "Std. Dev." means standard deviation.

1 *Table notes:* For all models, results were estimated from a sample of 2,003 individuals, 11,613 choice observations,
2 with an initial log-likelihood of -17279.16.

3