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

5 HIGHLIGHTS

- Model how subjective evaluation of existing modes influence autonomous mobility-ondemand (AMOD) adoption
 - Model impact of inertia from existing travel modes on AMOD choice
 - Find that subjective evaluations and inertia both predict mode choice
- Particularly, positive evaluations and current use of ridehailing are strongly predictive of AMOD choice
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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 current travel behavior are as or more important than demographics in determining intention to 17 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 Singapore to investigate how the subjective evaluation of existing travel modes (attitudes) and 20 inertia based on previous use of existing modes affect the adoption of an autonomous mobility-on-21 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, our results might suggest that how AVs are implemented and their similarity to existing modes 31 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

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Keywords: Autonomous vehicles; mode choice; mixed logit model; factor analysis; latent
 variables; inertia

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1 **1. INTRODUCTION**

2 As autonomous vehicle (AV) technology continues to advance, it is important to understand how 3 it will impact our existing transportation systems. However, many factors make these future 4 impacts uncertain, including how the technology will be deployed and regulated, whether 5 infrastructure will change along with the vehicles, how service models and markets will adapt, and 6 how individual consumers will adopt the technology, potentially changing their existing travel 7 behavior (Fagnant and Kockelman, 2015). Given that AVs have not yet moved beyond 8 development and testing to full commercial deployment, analyzing the long-term effects of AVs 9 on transportation systems and travel behavior rely on modeling of potential future scenarios (e.g., 10 Basu et al., 2018; Nieuwenhuijsen et al., 2018; Milakis et al., 2017; Gruel and Stanford, 2016).

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12 One of the most pivotal aspects to consider in constructing these future scenarios is the adoption 13 behavior of individual travelers. Because adoption of emerging technologies is uncertain and

14 heterogeneous, consumers' perceptions of and intentions to use AVs have been an active area of

15 research in recent years. Since AVs are not yet commercially available, most studies make use of

16 hypothetical stated choice surveys to analyze people's willingness to pay for and likelihood to 17 adopt AVs (e.g., Gkartzonikas and Gkritza, 2019; Becker and Axhausen, 2017). Past studies have

18 found separately that attitudes towards AVs and existing travel behavior play a significant role in

19 predicting AV adoption (in addition to individual socio-demographics). However, no study to date

20 has looked at how people's perceptions and use of current travel modes both simultaneously

- 21 influence and help forecast AV adoption.
- 22

23 To address this research gap, this study analyzes the impact of people's perceptions and use of 24 current travel modes on the adoption behavior of AVs with a stated preference survey. In particular, 25 the study aims to answer the following questions:

- 26 • How does the subjective evaluations of existing travel modes influence AV adoption and 27 potential substitution patterns between different modes? 28
 - 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 31 of AV adoption as well as methodological state-of-practice regarding survey designs and 32 33 econometric models to analyze the problem.
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35 The study is conducted in Singapore, which is a world leader in adopting new transport 36 technologies and experimenting with different policy regulations and aims to be one of the first 37 markets to adopt AVs if they become commercially available (Abdullah, 2019). Specifically, we 38 consider the adoption of an autonomous mobility-on-demand (AMOD) service in which a fleet of 39 AVs are dynamically matched with trip requests. This is the form of AV deployment that the 40 Singapore Land and Transport Authority (LDA) has announced to pilot and deploy (Bhunia, 2017).

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42 The rest of this paper is organized as follows. Section 2 reviews existing literature on AV adoption 43 analysis; Section 3 discusses the survey design; Section 4 provides details on model formulation;

44 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. 45

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1 2. LITERATURE REVIEW

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

time and travel cost as well as attributes of the built environment are critical predictors of AV adoption (Gkartzonikas and Gkritza, 2019; Nodjomian and Kockelman, 2019; Shabanpour et al.,

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

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

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
- 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

A more limited number of studies have linked existing travel behavior—by private car, transit, biking, and walking—to their adoption of AMOD. Krueger et al. (2016) found that those who

travel exclusively by private car or taxi are more likely to adopt AMOD, and Haboucha et al. (2017)

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

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

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

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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) for a transportation application and Festinger, 1962 for a general theory of cognitive dissonance). 11 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 confirmatory factor analysis to estimate latent variables representing subjective evaluations of 17 existing travel modes and add them to the model. We incorporate existing use of travel modes as 18 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

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

29 **3.1 Survey Design**

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

35

In the RP portion of the survey, each respondent was first presented with a trip purpose—commute (to work or school), shopping (to grocery store or supermarket), or recreation/entertainment. The respondents were then asked to report the postal codes of trip origin (O) and destination (D), and the mode with which the trip was usually made. Based on the respondent's revealed OD, some attributes, including walking time, bus access walking time, bus in-vehicle time, ridehailing invehicle 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

Front End	INPUT origin and destinati postal code	on f	SELECT select most frequently visited station	•	MODE CHOICE - REVEALED select actual mode choice for the trip	_	MODE CHOICE - STATED select mode from hypothetical scenarios	SUBJECTIVE EVALUATIONS 7-point Likert-scale questions	DEMOGRAPHICS	
Back End	GEOCODE find the closest MF stations	π	GENERATE mode-specific trip attributes		DESIGN orthogonal SP scenarios with the addition of AV					

2 3 4 5

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

9 every respondent watched an introductory video before answering the SP questions.

	Static A	ttributes	Trip-Specific	e Attributes
Mode	Name	Levels	Name	Levels
Walk			Walk time	
Public transit (PT)	Cost (\$S)	0.5, 0.9, or 1.5	Walk time	_
	Wait time (min)	3, 5, or 10	In-vehicle time	DD magnance M
Ridehailing (RH)	Wait time (min)	1, 3, or 8	Cost	- RP response x
-			In-vehicle time	0.5, 1, 01 1.5
Autonomous mobility-	Wait time (min)	1, 3, or 8	Cost	
on-demand (AMOD)			In-vehicle time	

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

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12 Similar to the RP portion, there were static and trip-specific attributes in the SP choice experiment. The static attributes had three levels, with the median anchored to the market average and the 13 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 0.5 times the value given in the RP responses, respectively. For the AMOD service (not present in 17 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 generated, resulting in 27 scenarios. Six out of these 27 SP scenarios were randomly chosen for 21 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.

		Total Cost	Origin	Walk Ҟ (min)	Wait X (min)	In-vehicle	Destin.	Total Time
1. Walk	六	\$0.0	畲	30	n.a.	n.a.		30 min
2. Public Transit		\$1.3	畲	4	5	18		27 min
3. Ride Hailing		\$4 .0	俞	n.a.	3	12		15 min
4. Ride Hailing with AV	((\$5.0	畲	n.a.	3	8		11 min
5. Drive	.	\$4.0	畲	3	n.a.	9		12 min

3 Figure 2. Example interface for stated preference choice experiment

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

11 to "totally agree" (7).

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

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

Because there are clear differences between the sample and the population in certain demographic
categories, we calculate survey weights using iterative proportional fitting (IPF or raking). Weights
were calculated using the *anesrake* package in R (Pasek, 2018), which implements the American
National Election Study (ANES) weighting algorithm documented in (DeBell and Krosnick, 2009).

13 Convergence was reached so that weighted sample proportions exactly match the population

14 proportions for all characteristics listed in Table 3.

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

Socio-demographic	Bin	Sample (%)	Population (%)
characteristics			
Age (as percent of adult	20-29	29.1	17.5
population aged 20 or	30-39	24.6	18.5
older, 2017)	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	Not working or below 2,000	10.2	19.0
income (S\$) (2017)	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	Below secondary	0.3	29.3
(2016)	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	0	43.5	64.7
ownership (2017)	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 evaluations and inertia on the potential adoption of AMOD. The high-level model structure is 6 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 made in previous choice situations in SP responses. Then, these estimated factor scores and inertia 10 measures were entered into a mixed multinomial logit (MMNL) model, along with the 11 demographic and trip-specific attributes presented in the survey. The model was estimated using 12 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 16

Figure note: Rectangual boxes represent observed variables such as characteristics of respondents and attributes of 17 choice alternatives (modes), inertia variables, psychometric indicators, and mode choices are represented by

18 rectangular boxes; ovals represent latent variables such as utilities and subjective evaluations; solid arrows represent 19 structural equations; dashed arrows represent measurement equations. The CFA model and MMNL model were 20 estimated sequentially, with factor scores for each subjective evaluation latent variable treated as observed variables

21 in the choice model.

22 **4.1 Subjective Evaluations**

23 Respondent's subjective evaluations of existing travel modes—walking, public transit (PT),

ridehailing (RH), and driving-are estimated as latent variables based on responses to five 24

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

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).

13

14 Figure 4. Structure of the Confirmatory Factor Analysis models for the subjective

15 evaluation of existing travel modes



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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), $Q_m = \{$ 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)
$$Z_{nmk}^* = \theta_{0mk} + \theta_{1mk}A_{nm} + \eta_{mk}$$

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

7

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

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

11

12 **Eq. (3)**

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

14

16

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

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

19

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

21

where $E[\cdot]$ is the expectation. $f_{A_{nm}|Z}(\cdot)$ is the posteriori probability density function of A_{nm} . **Z** is the vector of all Z_{nmk} . $\Pr(\mathbf{Z} | A_{nm} = w)$ can be calculated as the product of all $\Pr(Z_{nmk} | A_{nm} = w)$. $f_{A_{nm}}(\cdot)$ is the prior probability density function of A_{nm} . Eq. 4 indicates that $A_{nm} = \hat{A}_{nm} + \delta_m$, where δ_m is an error term with mean of zero. In this study, we assume $\delta_m \sim \mathcal{N}(0, \sigma_m^2)$ for the 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 respondents' stated preferences. The definition of inertia was adapted from Cherchi et al. (2017) 32 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

The sequence of each question is labeled as choice situation *t*, where t = 0 for the RP question and $t = \{1, ..., 6\}$ 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,

4 5

6

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

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

10 The second type of the inertia accounts for the effect that as more inertia is formed if the mode is 11 selected more often in the panel data, and therefore is a function of the number of times that a 12 mode is selected in different choice situations by the same individual. Let I_{njt}^{H} represent the hazard 13 inertia of mode *j* for individual *n* in choice situation *t*, and it is assumed to have the inverse 14 Weibull distribution:

16 **Eq. (6)**
$$I_{njt}^{\mathrm{H}} = \left(FRE_{njt}\right)^{1-\gamma_j} \quad \forall j \in S, t \ge 1$$

17

18 where FRE_{njt} is the adjusted number of times mode *j* is selected from choice situations 0 (RP) to 19 t-1 for individual *n*. The adjustment is done on FRE_{njt} by increasing it one unit as the 20 respondent selects mode *j* and decreasing it one unit as the respondent switches to another mode 21 (Cherchi et al., 2017). Note that FRE_{njt} will not be further decreased when it reaches 0. $\gamma_j \in [0,1]$ 22 is the hazard function parameter (HFP) to be estimated.

23

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.

27 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:

- 35
- 36 Eq. (7)

37

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

38

39 Eq. (8)

 $1 U_{njt}^{SP} = V_{njt}^{SP} + \varepsilon_j^{SP}$

2

3

4 5

$$=\beta_{j}^{ASC} + \beta_{j}^{T}T_{njt} + \beta_{j}^{X}X_{n} + \sum_{m=1}^{4}\beta_{mj}^{A}(\hat{A}_{nm} + \delta_{m}) + \sum_{j'\in S}\beta_{j'j}^{L}I_{nj't}^{L} + \sum_{j'\in S}\beta_{j'j}^{H}I_{nj't}^{H} + \varepsilon_{jt}^{SP}$$

6 where U_{njt}^{SP} and U_{nj}^{RP} are the utility functions of the SP and RP, respectively. The subscript *t* in RP 7 utility function is ignored because there is only one RP choice situation and t = 0 for RP by 8 definition. β_j^{ASC} are the alternative-specific constants; T_{nj}^{RP} and T_{njt} are alternative-specific trip 9 attributes of mode *j*; X_n is the vector of socio-demographic variables of individual *n*; β_j^X , β_j^T , β_{mj}^A , 10 β_{jj}^L , and β_{jj}^H are the coefficients to be estimated; ε_j^{RP} and ε_{jt}^{SP} are the Gumbel-distributed error term 11 for the RP and SP questions, respectively. The scale of RP data (μ_{RP}) is normalized to 1 and the 12 scale of SP data is denoted as μ_{SP} , which will be estimated in the model.

13

14 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. 16 Thus, the probability for an individual *n* choosing mode *j* can be expressed by the following equation:

18 19 Eq. (9)

20
$$\Pr(Y_{nt} = j) = \int \Pr(Y_{nt} = j \mid \tilde{\delta}_j = w) \phi_{\tilde{\delta}_j}(w) dw = \int \frac{\exp(\mu V_{njt})}{\sum_{j'' \in C_n} \exp(\mu V_{nj''t})} \phi_{\tilde{\delta}_j}(w) dw$$

21

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.

26

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.

34 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:

37

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

39

where θ , β , σ and μ_{SP} are the coefficients to be estimated. T = 6 is the number of SP questions. 1 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 inhibitive. 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 the factor scores for each latent variable and each individual (i.e., \hat{A}_{nm}) are estimated using Eq 3. 17 In the second step, we estimate the MMNL with MSL, obtaining β , $\tilde{\sigma}_i$ and μ_{SP} . The model is

In the second step, we estimate the MMNL with MSL, obtaining β , $\tilde{\sigma}_j$ and μ_{SP} . The model is 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

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

27 the unrepresentativeness of our sample (see Appendix B).

28 **4.5 Evaluation Scenarios**

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

- 31
- M1 (base): Socioeconomic variables + mode attributes
- M2 (only subjective evaluations): Socioeconomic variables + mode attributes + subjective evaluations
- M3 (only inertia): Socioeconomic variables + mode attributes + inertia
- M4 (subjective evaluations + inertia): Socioeconomic variables + mode attributes + subjective evaluations + inertia
- 38
- 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.
- 41 the same framework.

1 5. RESULTS AND DISCUSSION

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

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**

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

- 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 R^2 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,
- the highest VIF score is 3.35, which means that no significant multicollinearity problems exist in
- including both the subjective evaluations and the inertia terms in the choice model. Therefore, we
- 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
- and repeated stated preference for a mode (hazard-inertia) can all play different roles in people's mode choice
- 30 mode choice.

31 Table 4. Pearson correlation coefficients (ρ) between and VIF of subjective evaluation and 22 inartia for each travel mode

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 ρ^2 . The values are presented in the

bottom panel of Table 5. For all metrics, model performances improved from M1 to M4, meaning

both subjective evaluations and inertia improved the explanatory power of the model. Among the

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

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)

	14	M2	2.42	M4
Parameter	MI	Base + subjective	M3	Base + subjective
	Base	evaluations	Base + inertia	evaluations + inertia
Alternative specific constants (B^{A}	isc)			
Walk	0.000 (fixed)	0.000 (fixed)	0.000 (fixed)	0.000 (fixed)
Public transport (PT)	-0.147 (0.108)	-0.056 (0.114)	0.690 (0.146) ***	0.761 (0.190) ***
Ridehailing (RH)	-0.616 (0.126) ***	-0.531 (0.126) ***	-0.450 (0.164) ***	-0.412 (0.183) **
Drive	0.103 (0.081)	0.199 (0.083) **	0.027 (0.114)	-0.089 (0.177)
AMOD	-0.697 (0.137) ***	-0.504 (0.147) ***	-0.425 (0.191) **	-0.470 (0.228) **
Subjective evaluations (\mathcal{B}_m^A)			× /	
Walk: Pro-walk	-	0.775 (0.065) ***	-	0.863 (0.108) ***
PT: Pro-walk	-	-0.048 (0.046)	-	-0.029 (0.090)
PT: Pro-PT	-	0.698 (0.068) ***	-	0.524 (0.089) ***
RH: Pro-RH	-	0.568 (0.047) ***	-	0.550 (0.069) ***
Drive: Pro-drive	-	0.597 (0.057) ***	-	0.577 (0.116) ***
AMOD: Pro-walk	-	0.027 (0.059)	-	0.184 (0.095) *
AMOD: Pro-PT	-	-0.054 (0.081)	-	-0.098 (0.088)
AMOD: Pro-RH	-	0.416 (0.050) ***	-	0.386 (0.071) ***
AMOD: Pro-drive	-	0.039 (0.053)	-	-0.055 (0.075)
Inertia (lagged $\boldsymbol{\beta}_{i}^{L}$ and hazard $\boldsymbol{\beta}_{i}^{L}$	H)			
Walk: Lag inertia-walk	-	-	-0.485 (0.089) ***	-0.592 (0.110) ***
Walk: Hazard inertia-walk	-	-	0.813 (0.079) ***	0.831 (0.096) ***
PT: Lag inertia-walk	-	-	-0.926 (0.090) ***	-1.200 (0.146) ***
PT: Hazard inertia-walk	-	-	0.222 (0.052) ***	0.194 (0.067) ***
PT: Lag inertia-PT	-	-	-0.979 (0.072) ***	-1.340 (0.138) ***
PT: Hazard inertia-PT	-	-	0.780 (0.073) ***	1.200 (0.155) ***
RH: Lag inertia-RH	-	-	1.110 (0.106) ***	1.230 (0.147) ***
RH: Hazard inertia-RH	-	-	0.772 (0.085) ***	0.944 (0.127) ***
Drive: Lag inertia-drive	-	-	0.201 (0.367)	0.240(0.591)
Drive: Hazard inertia-drive	-	-	1.330 (0.136) ***	2.430 (0.377) ***
AMOD: Lag inertia-walk	-	-	0.000 (fixed)	0.000 (fixed)
AMOD: Hazard inertia-walk	-	-	-0.120 (0.066) *	-0.100 (0.070)
AMOD: Lag inertia-PT	-	-	0.364 (0.091) ***	0.404 (0.106) ***
AMOD: Hazard inertia-PT	-	-	0.074 (0.044) *	0.101 (0.052) *
AMOD: Lag inertia-RH	-	-	1.410 (0.140) ***	1.600 (0.191) ***
AMOD: Hazard inertia-RH	-	-	0.507 (0.072) ***	0.665 (0.106) ***
AMOD: Lag inertia-drive	-	-	0.764 (0.247) ***	0.702 (0.281) **
AMOD: Hazard inertia-drive	-	-	0.157 (0.102)	0.254 (0.124) **
Mode attributes (β_T)				· · · · · · · · · · · · · · · · · · ·
Walk: Walking time (min)	-0.050 (0.003) ***	-0.050 (0.003) ***	-0.046 (0.003) ***	-0.054 (0.004) ***
PT: Travel cost (\$SG)	-0.221 (0.018) ***	-0.240 (0.021) ***	-0.278 (0.024) ***	-0.396 (0.046) ***
PT: In-vehicle time (min)	-0.020 (0.001) ***	-0.020 (0.001) ***	-0.022 (0.002) ***	-0.027 (0.003) ***
PT: Waiting time (min)	-0.031 (0.004) ***	-0.031 (0.004) ***	-0.034 (0.005) ***	-0.043 (0.008) ***
PT: Walking time (min)	-0.034 (0.003) ***	-0.035 (0.003) ***	-0.035 (0.003) ***	-0.047 (0.005) ***
RH: Travel cost (\$SG)	-0.061 (0.005) ***	-0.065 (0.005) ***	-0.073 (0.006) ***	-0.092 (0.009) ***
RH: In-vehicle time (min)	-0.028 (0.003) ***	-0.030 (0.003) ***	-0.032 (0.004) ***	-0.046 (0.006) ***

	M1	M2	M2	M4
Parameter	Pasa	Base + subjective	NIJ Pasa inortia	Base + subjective
	Dase	evaluations	Dase + mertia	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 (<i>B</i> _w)	0.013 (0.007)	0.010 (0.000)	0.015 (0.000)	0.001 (0.00)
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(0.034)	-0.032(0.073)	0.099 (0.007) 0.041 (0.087)	0.025(0.111)
PT: Single	-0.002(0.071)	-0.052(0.075)	0.041(0.037) 0.126(0.070)	0.023(0.111)
PT: Driver license	0.002 (0.000)	0.003(0.003) 0.171(0.054)***	0.120(0.077) 0.130(0.063)**	0.208(0.104)
DT: Chinese	-0.130(0.051)	-0.171(0.054)	-0.139(0.003)	-0.101(0.085)
PT: Commute trip	-0.013(0.004)	-0.007(0.007)	-0.010 (0.060)	0.052(0.104)
	0.727(0.062)	0.723(0.000)	0.700(0.079)	0.933 (0.120)
PT: Full-time job	0.003 (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 $< SGS 4 000$	-0.151 (0.098)	-0.121 (0.100)	-0.003(0.132)	0.086(0.203)
Drive: Income $>$ SG\$ 12 000	$0.131(0.090)^{*}$	$0.121(0.100)^{*}$	0.003(0.132) 0.157(0.108)	$0.259(0.157)^*$
Drive: Single	0.144 (0.004)	0.142(0.004) 0.165(0.003)*	0.157(0.100) 0.065(0.124)	0.223(0.137)
Drive: Driver license	0.007(0.093)	0.100 (0.093) **	0.003(0.124) 0.027(0.114)	-0.089(0.177)
Drive: Chinasa	0.103(0.001) 0.082(0.105)	0.139(0.003) 0.138(0.106)	0.027(0.114) 0.120(0.141)	-0.089(0.177)
Drive: Commute trip	-0.082(0.103) 0.427(0.072)***	-0.138(0.100) 0.206(0.074)***	-0.120(0.141)	-0.242(0.211)
Drive. Commute trip	0.427(0.073)	0.390(0.074) 0.074(0.070)	0.460(0.101)	0.019(0.134)
Drive: Full-time job	-0.034 (0.078)	-0.074(0.079)	0.000(0.103)	-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)	0.1/4 (0.080)	0.123 (0.105)	0.075 (0.159)
Drive: Car owner	0.411 (0.137)	0.4/8 (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.

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

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 from use of the existing mode did not always lead to a greater likelihood of choosing it in the 11 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 doing so by choice. On the other hand, the choices to walk or take public transit were negatively 15 predicted by existing use of those modes. Individuals who were walking and taking public transit 16 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

transit, and then walking. All else being equal, individuals who currently use ridehailing and drive

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

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 piece of information for decision-making and evaluate latter scenarios with respect to the previous 10 ones. In other words, respondents may have related subsequent choice scenarios to a previous one, 11 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 coefficient for hazard inertia is strongly positive for ridehailing and negative for walking. The 15 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)**

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

26

27 In general, we find that positive evaluations of an existing mode contribute to a greater likelihood of choosing that mode. For example, those who had stronger positive evaluations of walking, 28 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
- 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

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

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 a full-time job are found to be more likely to take ridehailing (similar to findings by Moody and 35 Zhao, 2020) and AMOD. When it comes to the effect of education on AV mode choice, some 36 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

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

- people who self-report as Chinese ethnicity are less likely to take ridehailing and AMOD.
- 8

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

- 15 license, is not significantly predictive of AMOD choice.
- 16
- Finally, when it comes to trip purpose, we find that all modes are preferred over walking for commuting trips, with the most preferred mode being public transport.

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
- model as modal inertia terms, measuring a respondent's tendency to stick to their current mode of
- travel. A mixed logit choice model was estimated to investigate how subjective evaluations and
- use of existing modes separately and simultaneously affect individuals' mode choice when a new
- 30 autonomous mobility-on-demand (AMOD) service is introduced.
- 31

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

- 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

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

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 people will choose the newly introduced travel mode. The study found that people familiar with 11 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 inertia on different AV implementations may corroborate or challenge the interpretation of the 26 27 model results presented in this study. Furthermore, research could consider how subjective evaluation and current use of existing travel modes influence AV choice in other settings or for 28 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 important to observe actual user adoption of these services and compare these revealed preferences 32 33 with previous stated preference studies.

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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 single factor. To ensure convergent validity, we want the majority of the item variances to be 6 explained by the single factor (standardized factor loading of > 0.70 and an R² > 0.5) as suggested 7 by Kline (2016). While this threshold was not met for all items, they did meet a more practical cut-8 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	\mathbb{R}^2
Pro-walk	I think walking feels safe	0.511	0.261
	I think walking is comfortable	0.678	0.460
	I think walking is a reliable mode	0.728	0.530
	I think walking feels easy	0.792	0.628
	I enjoy walking	0.895	0.802
	correlation between errors for safe and reliable	0.336	
Pro-PT	I think taking public transport feels safe	0.532	0.283
	I think taking public transport is comfortable	0.675	0.456
	I think public transport is a reliable mode	0.763	0.581
	I think taking public transport is easy	0.720	0.519
	I enjoy taking public transport	0.898	0.807
Pro-RH	I think ridehailing feels safe	0.686	0.470
	I think ridehailing is comfortable	0.769	0.592
	I think ridehailing is a reliable mode	0.816	0.665
	I think ridehailing is easy	0.758	0.575
	I enjoy ridehailing	0.811	0.658
Pro-drive	I think driving feels safe	0.655	0.429
	I think driving is comfortable	0.794	0.630
	I think driving is a reliable mode	0.821	0.675
	I think driving is easy	0.872	0.761
	I enjoy driving	0.864	0.747

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

2 **Divergent Validity**

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

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				
РТ	0.737	1.000			
RH	0.288	0.589	1.000		
Drive	0.314	0.326	0.442	1.000	

17

18 We additionally consider the MIs among the latent variables and their indicators. We find that

there are only a few MIs large enough to suggest potential cross-loading of indicators among latent

20 variables. However, given the moderate model fit without these cross-loadings, we do not include

21 them when estimating the correlations above.

22 Reliability

Finally, we estimate three common reliability indices for our latent variables: Cronbach's alpha (α), composite reliability (or Ω) and maximal reliability (H). For these reliability calculations, we treat our ordinal 7-point Likert scale indicators as a continuous as an approximation. We find that

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

1

2 APPENDIX B: MODEL ESTIMATION RESULTS WITH SAMPLE WEIGHTS

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

		MO		M4
D	M1		M3	
Parameter	Base	Base + subjective	Base + inertia	Base + subjective
	(0450)	evaluations		evaluations + inertia
Alternative specific constants	$(\boldsymbol{\beta}^{ASC})$			
Walk	0.000 (fixed)	0.000 (fixed)	0.000 (fixed)	0.000 (fixed)
Public transport (P1)	-0.398 (0.110)	-0.325 (0.110)	0.545 (0.130)	0.454 (0.161)
Ridehailing (RH)	-0.829 (0.127)	-0.610 (0.124)	-0.571 (0.143)	-0.543 (0.166)
Drive	0.163 (0.112)	0.405 (0.110)	0.116 (0.133)	0.098 (0.216)
AMOD	-0.992 (0.147)	-0.835 (0.161)	-0.721 (0.178)	-0.773 (0.229)
Subjective evaluations $(\boldsymbol{\beta}_m^A)$				***
Walk: Pro-walk	-	1.060 (0.075)	-	0.891 (0.107)
PT: Pro-walk	-	0.077 (0.055)	-	0.126 (0.080)
PT: Pro-PT	-	0.638 (0.053) ***	-	0.499 (0.085) ***
RH: Pro-RH	-	0.619 (0.046) ***	-	0.588 (0.071) ***
Drive: Pro-drive	-	0.544 (0.069) ***	-	0.446 (0.139) ***
AMOD: Pro-walk	-	0.141 (0.077) *	-	0.272 (0.093) ***
AMOD: Pro-PT	-	-0.009 (0.077)	-	-0.078 (0.092)
AMOD: Pro-RH	-	0.426 (0.052) ***	-	0.374 (0.072) ***
AMOD: Pro-drive	-	-0.103 (0.068)	-	-0.056 (0.086)
Inertia (lagged $\boldsymbol{\beta}_{i}^{L}$ and hazar	$d \boldsymbol{\beta}_i^H$)			
Walk: Lag inertia-walk	-	-	-0.440 (0.081) ***	-0.534 (0.102) ***
Walk: Hazard inertia-walk	-	-	0.880 (0.079) ***	0.913 (0.099) ***
PT: Lag inertia-walk	-	-	-1.010 (0.088) ***	-1.130 (0.138) ***
PT: Hazard inertia-walk	-	-	0.270 (0.054) ***	0.266 (0.067) ***
PT: Lag inertia-PT	-	-	-0.942 (0.068) ***	-1.110 (0.124) ***
PT: Hazard inertia-PT	-	-	0.797 (0.071) ***	1.080 (0.157) ***
RH: Lag inertia-RH	-	-	1.160 (0.103) ***	1.180 (0.138) ***
RH: Hazard inertia-RH	-	-	0.748 (0.081) ***	0.911 (0.135) ***
Drive: Lag inertia-drive	-	-	0.182 (0.310)	0.160 (0.549)
Drive: Hazard inertia-drive	-	-	1.210 (0.143) ***	2.450 (0.500) ***
AMOD: Lag inertia-walk	-	-	0.000 (fixed)	0.000 (fixed)
AMOD: Hazard inertia-walk	-	-	-0.108 (0.067)	-0.110 (0.074)
AMOD: Lag inertia-PT	-	-	0.374 (0.087) ***	0.403 (0.104) ***
AMOD: Hazard inertia-PT	-	-	0.019 (0.044)	0.043 (0.051)
AMOD: Lag inertia-RH	-	-	1.240 (0.138) ***	1.310 (0.177) ***
AMOD: Hazard inertia-RH	-	-	0.571 (0.074) ***	0.712 (0.119) ***
AMOD: Lag inertia-drive	-	-	0.819 (0.182) ***	0.851 (0.217) ***
AMOD: Hazard inertia-drive	-	-	0.016 (0.119)	0.067 (0.150)
Mode attributes $(\boldsymbol{\beta}_{T})$				
Walk: Walking time (min)	-0.058 (0.003) ***	-0.055 (0.003) ***	-0.046 (0.003) ***	-0.053 (0.004) ***
PT: Travel cost (\$SG)	-0.247 (0.019) ***	-0.245 (0.018) ***	-0.261 (0.022) ***	-0.346 (0.045) ***
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 (0.001) ***	-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 (\$\$G)	-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 (0.003)	-0.051(0.007)
DU: Waiting time (min)	-0.037(0.004) 0.043(0.007) ***	-0.037(0.004)	-0.037(0.004) 0.020(0.007) ***	-0.031 (0.000)
$rac{1}{1}$ watting tille (fiffi)	-0.043(0.007) 0.140(0.008)***	-0.030 (0.000)	-0.029(0.007) 0.115(0.008)***	-0.030 (0.009)
Drive. In vehi-1- time (m)	-0.140(0.000)	-0.129(0.007)	-0.113(0.000)	-0.103(0.022) 0.064(0.011)***
Drive: in-venicie time (min)	-0.037 (0.003)	-0.041 (0.005)	-0.045 (0.006)	-0.004 (0.011)
Drive: Walking time (min)	-0.097 (0.018)	-0.086 (0.018)	-0.068 (0.021)	-0.102 (0.035)

	M1	M2	M2	M4
Parameter	IVI I Daga	Base + subjective	NIS Dece Linertie	Base + subjective
	Dase	evaluations	Dase + merua	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	0.036(0.057) 0.246(0.055)***	0.147 (0.053) ***	0.430 (0.001)	0.309(0.097)
PT: High education ²	0.117 (0.055) **	$0.147(0.053)^{*}$	0.210(0.057) 0.031(0.058)	0.200(0.074)
PT: Aga > 60	0.117(0.055) 0.020(0.067)	0.102(0.055) 0.105(0.065)	0.031(0.038) 0.088(0.073)	0.000(0.071)
F 1. Age > 00	-0.020(0.007)	-0.103(0.003)	0.066(0.073) 0.002(0.067)	0.054(0.090)
PT: Age < 33	0.031(0.002)	-0.027(0.001)	-0.003(0.007)	-0.030 (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)
P1: 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) ***	0.129(0.135)	0.530 (0.280) *
Drive: Male	-0.021(0.093)	-0.126(0.091)	-0.042(0.100)	-0.091(0.169)
Drive: Have kid under 18	-0.021(0.000)	-0.120(0.001) 0.147(0.131)	-0.042(0.107) 0.143(0.158)	-0.091(0.109) 0.228(0.248)
$\Delta V_{\rm c}$ income $\leq SC^{\text{S}} = 4.000$	0.209(0.130)	0.147(0.131) 0.202(0.080) ***	0.143(0.138) 0.217(0.085)**	0.226 (0.248)
AV: Income $< SG$ 4,000$	-0.518(0.085)	-0.302 (0.080)	-0.217(0.083)	-0.220(0.097)
AV: Income > $SG5 12,000$	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	M2 Base + subjective	M3	M4 Base + subjective
i diulletei	Base	evaluations	Base + inertia	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 p 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.

Table notes: For all models, results were estimated from a sample of 2,003 individuals, 11,613 choice observations, 1

2 with an initial log-likelihood of -17279.16.

3

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

AUTHOR CONTRIBUTION STATEMENT

Baichuan Mo: data curation, methodology formal analysis, writing – original draft; writing – review & editing; **Qingyi Wang:** writing – original draft, writing – review & editing; **Joanna Moody:** project administration, formal analysis, writing – original draft, writing – review & editing; **Yu Shen:** conceptualization, data curation; **Jinhua Zhao:** conceptualization, funding acquisition, supervision.