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Fancy sharing an air taxi? Uncovering the impact of variety seeking on the demand for new shared mobility services

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Abstract Shared mobility has been burgeoning in recent years and there is growing interest in replicating ground-based shared-mobility services in the air. This is expected to significantly reduce travel time and alleviate traffic congestion. The entry of a new travel service (e.g. air taxi) results in changes in conditions of the transport system and induces changes in individual mode choices. In this paper, we examine the impact of variety-seeking on the adoption of such new modes and services. We distinguish between two specific effects associated with variety-seeking, namely novelty-seeking (i.e. the inclination to adopt new modes) and alternation (i.e. the inclination to vary ones' behaviour regularly by selecting different modes continuously). This paper makes use of stated-choice data provided by Uber, and examines travel demand for various shared mobility services (including the upcoming air taxi service) and conventional modes. We propose a new latent class model with a latent variable of variety-seeking. Specifically, intra-individual preference heterogeneity is accommodated on top of inter-individual preference heterogeneity to control for the alternation effect. The results suggest that novelty seekers are more likely to fall into the class with higher probabilities to switch from existing modes to the new air taxi service than novelty avoiders, and alternation seekers are more likely to belong to the class with higher probabilities to exhibit intra-individual preference heterogeneity than alternation avoiders. This

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paper therefore provides empirical evidence about market shares when the new air taxi service enters the market and helps to identify target customers.

Keywords shared mobility · intra-individual preference heterogeneity · latent variable latent class model · variety-seeking · vertical take-off and landing

1 Introduction

1.1 Research background

We are living in an era of unprecedented change where science and technologies evolve rapidly and shape different aspects of our life. Shared mobility, being a crucial facet of the prevalent shared economy, has been burgeoning in the recent decade. According to Shaheen et al. (2016), shared mobility refers to *"an innovative transportation strategy that enables users to gain short-term access to transportation modes on an as-needed basis."*

Shared mobility has different forms depending on which type of mode is shared (Shaheen et al., 2016). For example, car-sharing/bike-sharing enables users to have temporary access to automobiles/bicycles provided by car-sharing/bike-sharing operators (e.g. DeMaio, 2009; Shaheen et al., 2010; Bardhi and Eckhardt, 2012). Ride-sharing usually includes carpooling and vanpooling, which involve sharing a car or a van among several road users for the sake of reduced travel cost per person (e.g. Agatz et al., 2012; Furuhata et al., 2013). Ride-sourcing, which is also known as Transportation Network Company (TNC) or ride-hailing, usually provides passengers with a demand-responsive travel service which can be booked through mobile apps shortly prior to the departure time and therefore can free passengers from street hailing (e.g. Cramer and Krueger, 2016; Dias et al., 2017). Examples like Uber, Lyft and Didi provide a variety of ride-sourcing services to cater for different travel needs. For instance, passengers can choose whether to split the ride with strangers at a reduced cost, choose the capacity of the vehicle, choose whether to ride in a luxury car at a higher cost, etc.

Shared mobility services like ride-sharing, bike-sharing, and car-sharing are expected to slow down the increase of personal vehicle ownership, reduce traffic emissions and improve the efficiency of transport networks as a whole due to the improved utilisation of transport resources. However, whether ride-sourcing can significantly contribute to reducing traffic congestion is still unclear. This is mainly due to the concern that although ride-sourcing services can provide demand-responsive trips to facilitate people's travel, they may in the meantime result more trips overall and greater congestion (Hensher, 2018; Jin et al., 2018; Dong et al., 2018). In fact, gridlock remains a severe challenge especially in large urban centres. The latest Global Traffic Scorecard suggests that Americans lost 97 hours in congestion, costing each driver \$1,348 annually; whereas congestion in the UK caused each road user 178 hours of extra travel, costing £1,317 annually on average (INRIX, 2018).

Recently, the concept of shared mobility has been extended to air travel by utilising the vertical dimension as a revolutionary way out. The concept of "Urban Air Mobility" (UAM) has been emerging and gaining substantial research and investment interest. For example, Uber Elevate plans to launch its "UberAIR" service with commercial flight operations in Dallas-Fort Worth and Los Angeles in 2023; Airbus is leading the European commission's Urban Air Mobility Initiative, and targets at establishing and expanding the UAM network encompassing air shuttle, air taxi and air ambulance, each fitting a specific area of the wider UAM spectrum (Airbus, 2018).

Urban Air Mobility describes an air transportation system that enables on-demand, point-to-point and highly automated passenger or package-delivery air travel services at a low altitude within and around populated urban areas (Goyal, 2018). It is expected to significantly reduce travel time and mitigate traffic congestions on land. Specifically, electric or hybrid Vertical Take-off and Landing (VTOL) is recognised as the major type of aerial vehicles for UAM in the near future[1]. Also, the deployment of VTOL would not take up much valuable urban space for constructing "airports", "runways" etc, as rooftops of high buildings can be transformed into take-off and landing pads. Additionally, autonomous VTOL is beneficial to solve a shortage of pilots. Ultimately, UAM system could enable travellers to find an "air taxi" nearby through mobile apps and possibly to share the space and travel cost with other air-poolers on the same aerial vehicle, just like ride-sourcing service on land.[2]

1.2 Motivations and objectives

Mode choice studies between air and other modes (e.g. high-speed rail) for medium-to-long distance intercity travel have been conducted widely (e.g. Park and Ha, 2006; Román et al., 2007; Hess et al., 2018). Regarding urban travel, air has rarely been treated as an option as scheduled airline services are usually considered not competitive for short-distance travel. Nevertheless, the requirement for developing urban air mobility entails examining the travel demand for the new air taxi service.

The entry of a new mode leads to changes in the transport system, which may induce changes in individual mode choice behaviour. This requires fit-for-purpose empirical analyses to understand individual preferences and the travel demand for the new mode. However, there is a lack of such empirical evidence

[1] On-demand helicopter platforms already exist (e.g. Voom by Airbus in São Paulo and Mexico City). However, it is recognised that distributed electric propulsion and autonomous operation technologies, which are features of VTOL, are the key to address the major barriers to large-scale commercialised operation of UAM, such as safety, noise, emission and vehicle performance (Holden and Goel, 2016).

[2] Air-taxi is different from "flight-sharing". The latter (e.g. Wingly, Coavmi) allows certified private pilots to carry passengers such that the travel cost could be split among passengers including the pilots. In the European Union, flight-sharing is allowed on a non-commercial basis (EASA, 2018), whereas flight-sharing has been completely banned in U.S. which has caused much criticism (Koopman and Dourado, 2017).

in the context of air taxi. Some studies calibrated (rather than estimated) a multinomial logit model based on existing travel surveys which excluded the new on-demand air service, and then applied the obtained coefficients to compute aggregate mode shares for the new market with the hypothetical on-demand air service (e.g. Pu et al. 2014; Joshi et al. 2014; Baik et al. 2008). Thus, empirical analysis is needed to verify the assumptions about sensitivities towards various level-of-service attributes and explain the behavioural mechanisms behind individual choices. Peeta et al. (2008) estimated a binary choice model based on stated choice data to analyse the probability of switching to the new on-demand "very light jet" service. More recently, Fu et al. (2018) used stated choice data to examine preferences towards private car, public transit, autonomous vehicle and autonomous VTOL air taxi. To the best of our knowledge, there are no other empirical analyses on the matter of exploring the preferences for on-demand aerial services, particularly in the new context of Urban Air Mobility, where air taxi is expected to be powered by (autonomous) VTOL vehicles.

Individuals' preferences may present unique features in this new context compared to choice scenarios where all alternatives are familiar, as some intangible factors might affect mode choices. Specifically, we deem variety-seeking tendencies would affect mode choice in this context. Variety-seeking behaviour suggests changes can be "*inherently satisfying*" (McAlister and Pessemier, 1982) and "*utility can be derived from change itself*" (Givon, 1984). Besides, variety-seeking tendencies can be driven/reflected by two aspects, i.e. novelty-seeking and alternation-seeking (Ha and Jang, 2013). That is, while some people prefer to stick to old habits and resist changes and uncertainty, others favour unfamiliarity and novelty (e.g. new technology). Besides, while unfamiliarity to the new alternative might limit the ability of some respondents to fully evaluate choice tasks, the desire for alteration would lead others to choose a wider range of different alternatives. Although both aspects have been widely addressed in consumer and psychology research, they are rarely accommodated in discrete choice analyses using stated choice data.

Given this, the present paper aims at providing empirical evidence on mode choice and travel demand in the context of the new on-demand VTOL service, i.e. air taxi. We use stated choice data encompassing air taxi as an alternative in hypothetical choice scenarios, together with other existing ground-based shared mobility services and conventional modes like cars and transit. Disaggregate mode choice models are estimated to retrieve people's preferences towards various level-of-service attributes and analyse the travel demand for the new service. Specifically, we explore the role of novelty-seeking aspect and alternation aspect of variety-seeking in a stated choice setting by addressing three key questions:

1. Whether variety seekers have a higher probability to show higher inclination to adopt the new service of interest?
2. Whether variety seekers are more likely than variety avoiders to exhibit preference instability over the course of completing the SC survey?

3. If the impact of variety-seeking is detected, what type of individuals are more likely to be variety-seekers?

The remainder of this paper is organised as follows. We describe how the survey was carried out and present a descriptive analysis of the data in the next section. Then, the methodology of constructing the 2L-LV-LC model is explained step by step, followed by a discussion of the estimation results. Conclusions are presented in the last section.

2 Survey and data

2.1 UberAIR service context

This paper makes use of stated choice (SC) data provided by Uber on mode choice amongst different alternatives including its upcoming on-demand electric VTOL air taxi service, i.e. UberAIR. It is expected to cut existing door-to-door travel times by an estimated 30% to 60% and create zero emissions and very low levels of noise. Flights may be shared with other riders, leading to a reduced cost per individual. Passengers will be able to book UberAIR services with the same mobile app as existing ground-based services. Moreover, Uber's air and ground services may be integrated and coordinated in the operation, such that passengers can book door-to-door trips through a single request and payment, and be driven by ground service like UberX to/from the UberAIR take-off/landing pads. Fig. 1 illustrates the UberAIR service.

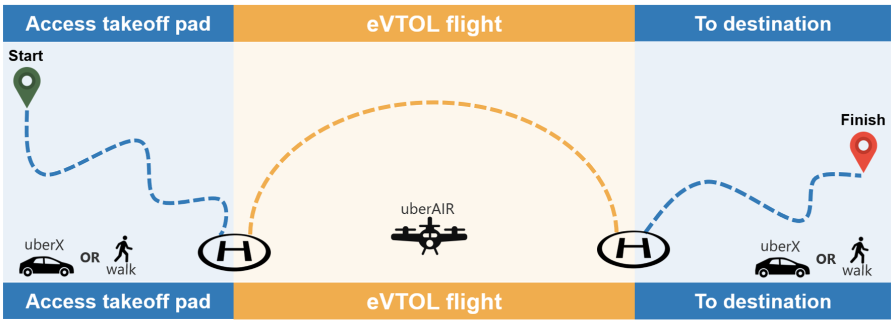

Fig. 1 Illustration of UberAIR service.

2.2 Questionnaire and respondent sampling

Since commercialised operation of UberAIR has not yet been realised, we cannot use revealed preference (RP) data to analyse people's preferences and trade-offs between different level-of-service attributes. Instead, a stated choice (SC) survey was conducted.

The survey was aimed at people living in the greater Dallas-Fort Worth or Los Angeles areas. Respondents were invited from four groups: LA online panel, DFW online panel, LA Uber customer list, and DFW Uber customer list. Respondents were sampled based on a series of screening questions with respect to their recent trip experience. If the respondent could not meet all of the criteria below, he or she would be disqualified. As to respondents from Uber customer lists, apart from the criteria mentioned below, they would also be disqualified if they had not used a ride-sourcing service in the month. The sampling criteria are:

- Home ZIP code match qualifying zip code for the targeted location (Dallas-Fort Worth or Los Angeles MSAs);
- Having used at least one of the following transportation modes and services within the last month (Personal or household vehicle; Rent vehicle; Car-share service; Bus; Light rail, metro, or subway; Commuter rail; Taxicab; Ride-sourcingc);
- Having completed at least one ground trip that took place in, around, or through the Dallas-Fort Worth/Los Angeles area;
- The trip was between 7-75 miles (one-way);
- The trip took at least 30 minutes in total (one-way);
- The trip purpose was one of the following purposes (Work commute; Other work-related business; Go to/from school; Go to/from airport; Shopping; Social or recreational; Entertainment event; Other personal business).

Disqualified respondents did not need to take the SC survey but were branched directly to the attitudes and socio-demographics so that they could finish the survey. Regarding qualified participants, their qualified trips would be regarded as the "reference trips" which would feed into the following SC survey.

The online questionnaire took around 15min to complete, and was mainly comprised of five components: 1) screening questions; 2) trip experience; 3) SC survey; 4) attitudinal statements; and 5) socio-demographic characteristics.

A total of 2,607 qualified respondents finished the whole survey, and Table 1 illustrates the sampling results. It can be found that different trip purposes were almost evenly distributed among the sample. Almost 60% of respondents used personal/household vehicle in the reference trip, whereas TNC service dominated the remaining 40% of sample. In contrast, much fewer people used rental vehicle/car-share service, taxicab, other ride-sourcing service or UberBLACK/UBerSELECT for their reference trips.

Before proceeding to further analysis, we stress that the individual-specific reference mode was always shown as the first alternative in the SC survey; meanwhile, UberX, UberPOOL and the new UberAIR were always presented in the SC survey. This leads to a situation where rental vehicle/car-share service, taxicab, other ride-sourcing service and UberBLACK/UberSELECT were very rarely available in the SC survey compared to the other modes. Therefore, in order to improve model efficiency, the discrete choice models included in this paper are all estimated on a subset of the qualified sample,

Table 1 Reference trips of sampled respondents

		Frequency	Percentage (out of 2607 respondents)
Trip purpose	Work commute	327	12.5%
	Other work-related business	334	12.8%
	Go to/from school	291	11.2%
	Go to/from airport	354	13.6%
	Shopping	314	12.0%
	Social or recreational	327	12.5%
	Entertainment event	328	12.6%
	Other personal business	332	12.7%
Trip mode	Personal/Household vehicle	1,540	59.1%
	Rental vehicle/Carshare	23	0.9%
	Transit	142	5.4%
	Taxicab	13	0.5%
	Other ride-sourcing Service	87	3.3%
	UberX	542	20.8%
	UberPOOL	195	7.5%
	UberBLACK/UberSELECT	65	2.5%

where only respondents using personal/household vehicle, transit, UberX or UberPOOL for their reference trips are involved. Consequently, 2,419 respondents are used for model estimation. This sample is of course not necessarily representative of the real world travelling population and it potentially biased towards existing users of Uber services. However, the purpose of the present study is exploratory and focused on specific behavioural traits rather than seeking representative findings for policy work.

2.3 Trip experience and socio-demographic characteristics

Each qualified respondent was required to provide further information about the reference trip, including departure time, total duration, delay experience, etc. These questions were tailored for respondents based on what the reference mode was. For example, if the reference mode was personal/household vehicle or ride-sourcing, then the respondent needed to suggest whether he/she experienced delay due to traffic congestion on the trip, how many people were in the vehicle on the trip, etc.

Table 2 summarises selected characteristics of the reference trip. Although the average trip distance varies across different reference modes, the average trip time calculated by Google for each reference mode group is approximately around 30min. However, due to delay time, waiting time and access/egress time, etc., the actual door-to-door trip time is much more diverse across reference modes, with transit taking the longest time (86min) and UberX costing just over half of the transit time (45min). Comparing personal/household vehicle group and UberX group, it can be found that with similar Google-calculated trip distance and trip time, UberX leads to a quarter less total travel time on average than personal/household vehicle, which might be due to the time saving from parking. Moreover, we can also discover that in comparison to UberPOOL, UberX can allow respondents to reach 8.1km farther with 6min less on average, which can be largely attributed to the time spent on matching other ride sharers and detouring to their destinations for UberPOOL trips.

Table 2 Descriptive summary of reference trip experience within the focus sample (total amount: 2419)

Reference mode	Personal/ Household vehicle	Transit	UberX	UberPOOL
Total respondents #	1,540	142	542	195
Respondents # who experienced delay	1,006 (65%)	NA	304 (56%)	134 (69%)
Average total delay time (min)	15	NA	11	17
Average Google-calculated trip distance (mile)	25.5	18	22.7	14.6
Average Google-calculated trip time (min)	33	27	32	26
Average total trip duration (min)	60	86	45	51

Table 3 describes the distribution of various socio-demographic characteristics. Respondents from the Dallas area and Los Angeles area are relatively similar. Females account for two thirds of the population. A sufficient number of respondents in each age band were approached, with a slight and steady decrease in proportion as age increases except for the youngest band. Over 93% of the respondents have at least one vehicle in the household. Additionally, while the official statistics show that the median household income (in 2017 inflation-adjusted Dollars) in 2017 is $54,501 in Los Angeles city and $47,285 in Dallas city (U.S. Cencus Bureau, 2018), our sample has a mean household income of $100,615 and a median household income of $62,500. This means that our sample contains a higher proportion of rich people than the census. Nevertheless, given that on-demand VTOL air taxi services would inevitably be more expensive, at least initially, than its ground competitors, we think approaching more high-income people is appropriate.

2.4 Stated choice survey

After a brief introduction of UberAIR, each respondent was presented with 10 hypothetical scenarios and was required to choose the most preferred alternative in each scenario. In each choice task, the first alternative was always related to the reference mode, and the last alternative was always UberAIR. While this potentially introduces ordering effects, this approach was outside the control of the analysis team. If a respondent used private vehicle or transit as the reference mode, then UberX and UberPOOL would serve as the second and the third alternatives respectively. In cases where UberX or UberPOOL was the reference mode, UberX or UberPOOL would only appear as the reference mode, i.e. only three alternatives would be available to be selected from. In order to ensure that the choice scenarios are closer to reality, the hypothetical choice scenarios were generated through a D-efficient experimental design and were framed around the individual-specific reference trips, where this in-

Table 3 Descriptive summary of the focus sample

Socio-demo characteristics	Level	Amount	Percentage (out of 2419 respondents)
Residence	Dallas	1,101	45.5%
	LA	1,318	54.5%
Gender	Female	1,616	66.8%
	Male	777	32.1%
	Prefer not to say	26	1.1%
Age	18-24	308	12.7%
	25-29	351	14.5%
	30-34	338	14.0%
	35-39	287	11.9%
	40-44	243	10.0%
	45-49	195	8.1%
	50-54	184	7.6%
	55-59	168	6.9%
	60-64	140	5.8%
	65-69	108	4.5%
	70 or older	97	4.0%
Household vehicle	None	151	6.2%
	1 vehicle	809	33.4%
	2 vehicles	962	39.8%
	3 vehicles	331	13.7%
	4 vehicles	114	4.7%
	5 or more vehicles	52	2.1%
Household annual income	<$35,000	479	19.8%
	$35,000-$49,999	335	13.8%
	$50,000-$74,999	416	17.2%
	$75,000-$99,999	368	15.2%
	$100,000-$149,999	341	14.1%
	$150,000-$199,999	153	6.3%
	$200,000-$249,999	75	3.1%
	$250,000-$499,999	62	2.6%
	>$500,000	38	1.6%
	Prefer not to say	152	6.3%

cluded additional UberAIR options. Fig. 2 gives an example of a stated choice task where UberPOOL was identified as the reference mode.

A total of 5 attributes, including “travel cost”, “in-vehicle time”, “flight time”, “access time”, and “egress time”, were involved in the SC survey, not all of which apply to every alternative. Travel cost was used to describe all of the alternatives expect for personal/household vehicle. In-vehicle time served as an attribute for all the existing ground-based modes, while flight time played a similar role in capturing the time spent within an aerial vehicle for UberAIR. Access time and egress time only applied to UberAIR. The upper part of Table 4 gives the median and mean values of each attribute for each alternative across observations. We notice that the distributions of travel time in the SC survey are comparable to the actual travel time in the reference trip shown in Table 2.

2.5 Attitudinal statements

In order to capture the influence of underlying psychometric constructs on choice behaviour, attitudinal statements were used to measure these unob-

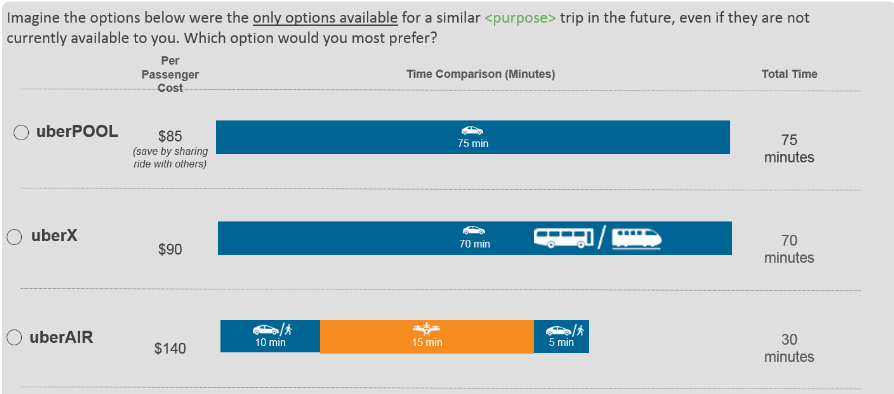

Fig. 2 Example of SC tasks.

Table 4 Summary of stated choice tasks

	Alternatives				
	private vehicle	transit	UberX	UberPOOL	UberAIR
Attributes (median, mean)					
travel cost ($)	-	(3, 8)	(35, 40)	(28, 32)	(70, 88)
in-vehicle time (min)	(58, 70)	(87, 99)	(51, 62)	(55, 68)	-
flight time (min)	-	-	-	-	(12, 15)
access time (min)	-	-	-	-	(7, 9)
egress time (min)	-	-	-	-	(7, 9)

served factors. Confirmatory factor analysis was conducted on 12 attitudinal statements as listed in Table 5, covering three constructs including "variety-seeking", "comfort of flying" and "dissatisfaction for status-quo". The statements were recorded in the form of a 5-point Likert scale , ranging from 1 being "strongly disagree" to 5 being "strongly agree".

Table 5 Attitudinal statements used for factor analysis.

#	Label (attitudinal statements)	Underlying constructs
1	I am comfortable with flying in a small aircraft	Comfort of flying
2	Traffic congestion is a major problem in my area	Dissatisfaction for status-quo
3	I wouldn't mind pooling with other people on eVTOL flights	(not loaded on any factors)
4	Uber is my preferred rideshare service	(not loaded on any factors)
5	I would use an autonomous vehicle if it is available	(not loaded on any factors)
6	I am comfortable with flying in a battery-powered aircraft	Comfort of flying
7	My current travel options for long-distance trips (50-100 miles) take too long	Dissatisfaction for status-quo
8	**I am one of the first to adopt new technology**	**Variety-seeking**
9	I usually take the cheapest mode of transportation available to me	(not loaded on any factors)
10	**I'm excited for eVTOL travel to become available in my area**	**Variety-seeking**
11	I wish travel times were more consistent and predictable in my area	Dissatisfaction for status-quo
12	I am concerned about my impact on the environment	(not loaded on any factors)

This paper is mainly interested in the role of variety-seeking in mode choices when a novel service enters the market, thereby we only discuss the statements loaded onto the construct of variety-seeking, which are statements #8 and #10 in Table 5. Their Chronbach's alpha estimate is 0.7 and Guttman's

Lambda 6 estimate is 0.54, suggesting relatively good internal consistency of these two statements. Table 6 shows the average value for each index that reflect variety-seeking based on the mode choice experience/ stated choices for each score band of the two attitudinal statements. It can be observed that stronger agreement with these two statements is related to a wider choice of ride-sourcing companies in the past and alternatives in the SC survey, as well as higher frequency of choosing the new UberAIR option and lower frequency of choosing the reference mode in the SC survey.

Table 6 Relation between the response of attitudinal statements and mode choice experience/ stated choices

	reflection of alternation		reflection of novelty-seeking	
Score	Ride-sourcing companies used in real life (mean in group)	Different SC alternatives chosen across 10 tasks (mean in group)	Times UberAIR chosen across 10 SC tasks (mean in group)	Times reference mode chosen across 10 SC tasks (mean in group)
statement #8				
1	0.6	1.6	0.9	7.5
2	0.8	1.8	1.3	6.1
3	1.0	2.0	1.7	5.0
4	1.3	2.2	2.8	3.8
5	1.5	2.3	3.7	1.9
statement #10				
1	0.6	1.4	0.7	7.3
2	0.7	1.6	0.6	7.2
3	0.9	1.9	1.2	5.6
4	1.1	2.2	2.6	4.3
5	1.5	2.3	3.8	2.2

3 Methodology

To analyse preferences towards various modes and attributes, as well as examine the role of variety-seeking, we carry out this study based on the assumption that inter-and-intra individual preference heterogeneity is attributed to variety-seeking tendencies. On the one hand, we associate the novelty-seeking aspect of variety-seeking with inter-individual preference heterogeneity, assuming that if variety-seeking is driven/reflected by novelty-seeking, then stronger variety-seeking would lead to stronger inclination to try the upcoming UberAIR service. On the other hand, we relate the alternation aspect of variety-seeking with intra-individual preference heterogeneity, presuming that if variety-seeking is driven/reflected by alternation, then stronger variety-seeking would contribute to higher propensity to exhibit unstable preference towards different alternatives.

An increasing number of studies have demonstrated the presence of intra-individual preference heterogeneity on top of inter-individual preference heterogeneity, i.e. preferences may not only vary across respondents, but also be unstable across choice tasks within a respondent (Hess and Rose, 2009; Hess and Train, 2011; Hess and Giergiczny, 2015; Becker et al., 2018). The common practice to account for inter-and-intra individual preference heterogeneity is to establish the model within a MMNL (mixed multinomial logit) framework by incorporating two layers of preference heterogeneity. That is, for a given preference parameter, a continuous random distribution across respondents and an additional continuous random distribution across the full cross-sectional observations are specified. However, this is achieved at a high computational cost because the calculation of the resulting log-likelihood involves integration at both layers (Hess and Train, 2011).

We resemble the conventional way of accommodating inter-and-intra heterogeneity within the framework of a latent class model, and further incorporate variety-seeking as a latent variable, forming a new two-layer Latent Variable Latent Class (2L-LV-LC) model. In this section, we illustrate how the new model is developed from basic models. Each model is established on the random utility maximisation (RUM) assumption that a respondent chooses the alternative with the highest utility.

3.1 Multinomial Logit (MNL) model

The Multinomial Logit (MNL) model (McFadden et al., 1973) has been widely used in understanding choice behaviour. It assumes a decision maker n can derive an unobserved utility U_{int} from alternative i in choice task t, which is consisted of a deterministic portion V_{int} and unobserved and random disturbance ε_{int}. The utility function is written as:

$$U_{int} = V_{int} + \varepsilon_{int} = \delta_i + \beta' x_{int} + \varepsilon_{int}, \tag{1}$$

where V_{int} typically follows a linear-in-parameter specification with an alternative-specific constant (ASC) δ_i. x_{int} is a vector of explanation variables for alternative i which is presented to respondent n in task t. A vector of to-be-estimated parameters β explain the sensitivities, and is treated as homogeneous across respondents and across choice tasks. The random error term ε_{int} is independently and identically distributed (IID) type I extreme value distribution.

Given J alternatives available in the choice set, respondent n will choose alternative i if $U_{int} \geq U_{jnt}, \forall j \in (1, \cdots, J)$. The probability of choosing alternative i out of the J alternative by respondent n in task t is thus given by:

$$P(y_{nt} = i) = \frac{e^{V_{int}}}{\sum_{j=1}^{J} e^{V_{jnt}}}. \tag{2}$$

The log-likelihood (LL) function can be obtained by taking the summation over respondents of the logarithm of the choice probability of a sequence of T choice tasks. The LL function has a closed form and is given by:

$$LL(y) = \sum_{n=1}^{N} \ln \left(\prod_{t=1}^{T} P\left(y_{nt} \mid \delta, \beta\right) \right). \tag{3}$$

3.2 Basic Latent Class (LC) model

MNL models assume all the preference heterogeneity is captured deterministically, e.g. through interactions between sensitivity parameters with socio-demographic characteristics. However, there exists preference heterogeneity that cannot be explained deterministically. Two typical methods to capture unobserved preference heterogeneity are the Mixed Multinomial Logit (MMNL) model (Boyd and Mellman, 1980; Cardell and Dunbar, 1980) and Latent Class (LC) model (Kamakura and Russell, 1989; Gupta and Chintagunta, 1994). While the former incorporates unobserved preference heterogeneity by using continuous distributions in parameters, the latter uses discrete distributions. Thus, the LC model does not need to make specific assumptions about the distribution of parameters.

The basic LC model is developed with an underlying MNL model described in section 3.1. Essentially, this basic LC model resembles the MMNL model with the assumption of inter-individual preference heterogeneity. It assumes that there are a finite number of classes S with different values for the parameters (including ASC vector δ_s and sensitivities vector β_s) in each class. In our case, we allow for two classes of respondents. This was found to give adequate gains in fit without undue increase in complexity and the number of parameters with the later two-layer model in mind. Thus, Eq. 1 can be replaced by:

$$U_{int,s} = V_{int,s} + \varepsilon_{int,s} = \delta_{i,s} + \beta_s' x_{int} + \varepsilon_{int,s}, \quad s \in (1, 2). \tag{4}$$

Following common practice, the class allocation model for two classes of respondents is specified in a binary logit form. We start from the basic specification which assumes the class allocation functions to be constant across respondents, then the probability π_s of a given respondent n falling into class s can be computed by:

$$\begin{aligned} \pi_1 &= \frac{e^{\gamma_1}}{e^{\gamma_1} + 1}, \\ \pi_2 &= 1 - \pi_1 \end{aligned} \tag{5}$$

such that $\sum_{s=1}^{S} \pi_s = 1$ and $0 \leq \pi_s \leq 1$, where γ_1 is the class-specific constant in the class allocation functions. The unconditional likelihood of making a sequence of choices by respondent n can be obtained by taking a weighted summation of the conditional likelihood given the class membership across classes, such that:

$$P(y_n) = \sum_{s=1}^{S} \pi_s \left(\prod_{t=1}^{T} P\left(y_{nt} \mid \delta_s, \beta_s\right) \right). \tag{6}$$

The log-likelihood function is given by: $LL(y) = \sum_{n=1}^{N} \ln P(y_n)$.

3.3 Two-layer Latent Class (2L-LC) model

Now we elaborate on how the new latent class model with two layers of heterogeneity is constructed to resemble the structure of the two-layer MMNL model. This is achieved by replacing the continuous mixture with discrete mixture at both inter-individual and intra-individual layers, which can substantially reduce the computational burden. Besides, alternation effect is controlled at the intra-individual layer to manifest preference variation across choice tasks. The model with latent variety-seeking is later discussed in the section 3.4.

3.3.1 Inter-individual layer

At the inter-individual layer, respondents are first of all segmented into S classes, each class carrying different preference parameters. Obviously, this is the same as the basic LC model in section 3.2. That is, a given respondent has a probability of π_s to belong to class s with ASC δ_s and sensitivities β_s which are specific to class s.

We continue to segment class s based on the assumption that while some individuals have consistent preference across choice tasks, others experience preference variation in the course of completing choice tasks. That is, for each class s, it is further segmented into a “no-intra” subclass with a probability of ϕ_1, and a “with-intra” subclass with a probability of ϕ_2. Herein, we use (s, q) to denote a subclass, with $q = 1$ standing for a “no-intra” subclass, and $q = 2$ for a “with-intra” subclass. As shown in Fig. 3, we eventually obtain four subclasses of respondents, among which $(1, 1)$ and $(2, 1)$ are “no-intra” subclasses with stable preference across tasks, whereas $(1, 2)$ and $(2, 2)$ are “with-intra” subclasses exhibiting heterogeneous preference over tasks.

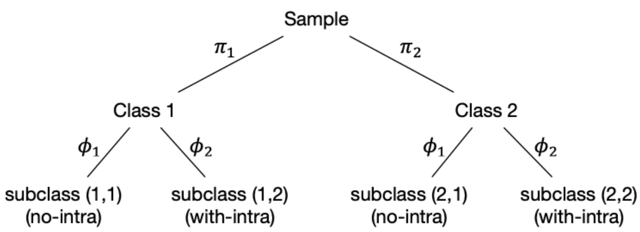

Fig. 3 Structure of the 2L-LC model (inter-individual layer).

Therefore, while keeping the class allocation model at upper part the same as in Eq. 5, we further adopt another binary logit model to determine the class allocation probability at the lower part such that:

$$\begin{aligned} \phi_1 &= \frac{e^{\lambda_1}}{e^{\lambda_1} + 1}, \\ \phi_2 &= 1 - \phi_1 \end{aligned} \tag{7}$$

where λ_1 is the constant specific to "no-intra" subclasses in the class allocation function and is generic in any class s.

As to the "no-intra" subclasses (i.e. $q = 1$), they are characterised with the baseline preference parameters δ_s and β_s at each choice. Thus, the utility function for alternative i given the class membership (s,1) is written as:

$$U_{int,(s,1)} = \delta_{i,(s,1)} + \beta'_{(s,1)} x_{int} + \varepsilon_{int,(s,1)} = \delta_{i,s} + \beta'_s x_{int} + \varepsilon_{int,(s,1)}, \quad s \in (1, 2), \tag{8}$$

and the conditional likelihood of observing a choice made by individual n at task t is:

$$P\left(y_{nt} \mid \delta_{(s,1)}, \beta_{(s,1)}\right) = P\left(y_{nt} \mid \delta_s, \beta_s\right). \tag{9}$$

As to the "with-intra" subclassess (i.e. $q = 2$), $\delta_{i,(s,2)}$ is not a constant value at the task level. We discuss how intra-individual preference heterogeneity is accommodated for these subclasses in section 3.3.2.

3.3.2 Intra-individual layer

Intra-individual preference heterogeneity is only accommodated for the "with-intra" subclasses (i.e. $q = 2$), by letting the ASC parameters $\delta_{(s,2)}$ shift around the baseline values by Δ at the observation level. The marginal utilities $\beta_{(s,2)}$ are fixed to the baseline values of β_s over tasks, i.e. no intra-individual heterogeneity in the marginal utility parameters. Fig. 4 presents the treatment at the intra-individual layer.

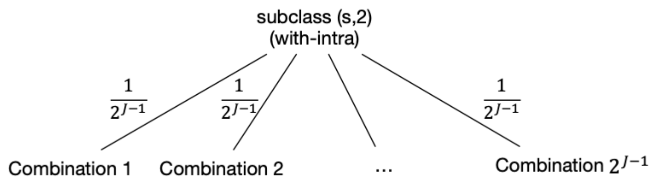

Fig. 4 Structure of the 2L-LC model (intra-individual layer).

More precisely, in order to manifest the variation of ASCs at the task level through discrete mixture rather than continuous distribution, we assume that each $\delta_{i,s}$ has an equal probability to either have an alternative-specific shift term Δ_i added or deducted, where Δ_i is kept generic in any class s. With this, the mean value of the ASC for alternative i given subclass membership $(s, 2)$ is maintained to be the same as in the corresponding "no-intra" subclass $(s, 1)$, which equates to $\delta_{i,s}$. Thus, we specify:

$$\delta_{i,(s,2)} = \delta_{i,(s,2),m_i} = \delta_{i,s} + \Delta_i(m_i == 1) - \Delta_i(m_i == 2), \tag{10}$$

where m_i is an alternative-specific indicator showing whether the shift term is added or deducted.

Given J alternatives in a choice set, alternative J is used as the base for normalisation with the corresponding ASC $\delta_{J,s}$ fixed to 0. Thus, we only account for intra-individual variation for the $J-1$ non-zero ASCs. In particular, we take into account all the possible combinations for the vector $\left(\delta_{1,(s,2),m_1}, \delta_{2,(s,2),m_2}, \cdots, \delta_{J-1,(s,2),m_{J-1}}\right)$, such that all the combinations amount to 2^{J-1} in total for a given individual at a given choice task.

Then we average the probability over the 2^{J-1} possible situations and use it as the conditional choice probability for respondent n at task t given the membership of a "with-intra" subclass, such that:

$$\begin{aligned} &P(y_{nt} \mid (\delta_{(s,2)}, \beta_{(s,2)})) \\ =&\frac{1}{2^{J-1}} \sum_{m_1=1}^{2} \sum_{m_2=1}^{2} \cdots \sum_{m_{J-1}=1}^{2} P\left(y_{nt} \mid \left(\delta_{1,(s,2),m_1}, \delta_{2,(s,2),m_2}, \cdots, \delta_{J-1,(s,2),m_{J-1}}\right), \beta_s\right), \end{aligned} \tag{11}$$

Combined with Eqs. 9 - 11, we can get the unconditional likelihood of observing a sequence of choices for a given respondent n by replacing Eq. 6 with:

$$P(y_n) = \sum_{s=1}^{S} \pi_s \left(\prod_{t=1}^{T} \left(\sum_{q=1}^{2} \phi_q P\left(y_{nt} \mid \delta_{(s,q)}, \beta_{(s,q)}\right) \right) \right). \tag{12}$$

3.4 Two-layer Latent Variable Latent Class (2L-LV-LC) model

Now we delve deeper into the drivers of inter-and-intra individual preference heterogeneity, i.e. variety-seeking. To reduce the risk of endogeneity and measurement errors, we treat variety-seeking as a latent variable. It is incorporated in two class allocation functions at the inter-individual layer, with two different parameters capturing the novelty-seeking effect and alternation effect, respectively. By doing so, people can be probabilistically segmented into different classes as functions of the latent construct (Hess et al., 2013; Motoaki and Daziano, 2015). Due to the concern that the two aspects of variety-seeking are related and intertwined, we do not explicitly specify two separate latent variables.

3.4.1 Structural equations for latent variable

We define a latent variable α_n to describe the underlying construct of variety-seeking in the structural equation. It is explained by selected socio-demographic characteristics in the structural equations as:

$$\alpha_n = \kappa' Z_n + \eta_n, \tag{13}$$

where η_n follows a standard Normal distribution across respondents. Z_n denotes the vector of selected covariates, with the vector κ measuring its impact on determining the value of the latent variable for respondent n.

3.4.2 Latent variables in class allocation functions

To account for the impacts of latent variety-seeking in the two-layer latent class model, we rewrite the class allocation probabilities specified in Eq. 5 and in Eq. 7 as:

$$\begin{aligned} \pi_{n,1} &= \frac{e^{\gamma_1+\tau_{\mathrm{NS}}\alpha_n}}{e^{\gamma_1+\tau_{\mathrm{NS}}\alpha_n}+1}, \\ \pi_{n,2} &= 1-\pi_{n,1} \end{aligned} \tag{14}$$

and

$$\begin{aligned} \phi_{n,1} &= \frac{e^{\lambda_1+\tau_{\mathrm{AT}}\alpha_n}}{e^{\lambda_1+\tau_{\mathrm{AT}}\alpha_n}+1}, \\ \phi_{n,2} &= 1-\phi_{n,1} \end{aligned} \tag{15}$$

such that the class allocation probabilities $\pi_{n,s}$ and $\phi_{n,q}$ vary across respondents. Parameters τ_{NS} and τ_{AT} measure whether and to what extent variety-seeking is reflected by novelty-seeking aspect and alternation aspect, respectively. If a higher value of the latent variable α_n is associated with a stronger variety-seeking tendency, then a significant positive τ_{NS} would suggest variety-seekers have higher probabilities of falling into the class with higher propensity to adopt the new UberAIR service, and a significant positive τ_{AT} would imply variety-seekers are more likely to belong to the class with preference heterogeneity over tasks.

Consequently, the conditional likelihood for the choice model component given the value of latent variety-seeking for respondent n can be written as:

$$P(y_n \mid \alpha_n) = \sum_{s=1}^{S} (\pi_{n,s} \mid \alpha_n) \prod_{t=1}^{T} \left(\sum_{q=1}^{2} (\phi_{n,q} \mid \alpha_n) \, P\left(y_{nt} \mid \delta_{(s,q)}, \beta_{(s,q)}\right) \right), \tag{16}$$

where $P\left(y_{nt} \mid \delta_{(s,1)}, \beta_{(s,1)}\right)$ and $P\left(y_{nt} \mid \delta_{(s,2)}, \beta_{(s,2)}\right)$ follow the specifications in Eq. 9 and Eq. 11, respectively.

3.4.3 Latent variables in measurement equations

In the meantime, the latent variable of variety-seeking is used in the measurement model components to explain four selected observable indicators.

Drawing on the concept of the Gini coefficient, we first calculate an inequality index $I_{n,\mathrm{GINI}}$ as a measure of variety in mode choice in real world travel experience by:

$$I_{n,\mathrm{GINI}} = \left(\sum_{k=1}^{K} \sum_{r=1}^{K} |g_{nk} - g_{nr}| \right) \Big/ \left(2 \sum_{k=1}^{K} \sum_{r=1}^{K} g_{nr} \right) \tag{17}$$

where g_{nk} stands for a "score of exposure" towards mode k for respondent n which takes a value of 2, 1, and 0 for the response of *"used mode k within* *the last month"*, *"used mode k over one month ago"* and *"never used before"* respectively. $K = 8$ as this exposure information is available for 8 modes, encompassing personal/household vehicle, rental vehicle, bus, light rail/metro/subway, commuter rail, taxicab, ride-sourcing service, and car-sharing service. Similar to the interpretation of the classical Gini coefficient, a higher value of the indicator $I_{n,\text{GINI}}$ is considered to be linked with greater inequality in exposure among different modes, meaning that the respondent has less diversity in mode choices and presumably only relies on a small set of modes.

$I_{n,\text{GINI}}$ is treated as a continuous dependent variable in a simple linear regression function (Ben-Akiva et al., 2002). Specifically, we centre it on 0 and then use a Normal density so that the mean of the Normal distribution does not need to be estimated (Hess and Stathopoulos, 2013), such that:

$$I_{n,\text{GINI}} - \overline{I_{\text{GINI}}} = \zeta_{\text{GINI}}\alpha_n + \sigma_{I_{\text{GINI}}}\xi_{I_{\text{GINI}}}, \tag{18}$$

with $\overline{I_{\text{GINI}}}$ being the mean of $I_{n,\text{GINI}}$ across individuals. Parameter ζ_{GINI} measures the role of latent variety-seeking in explaining the responses towards the "Gini" indicator. The variance is estimated by $\sigma_{I_{\text{GINI}}}$, with $\xi_{I_{\text{GINI}}}$ distributed a standard Normal. Thus, the likelihood of observing $I_{n,\text{GINI}}$ is given by:

$$P(I_{n,\text{GINI}} \mid \alpha_n) = \frac{1}{\sigma_{I_{\text{GINI}}}\sqrt{2\pi}}\left(e^{-\frac{\left(I_{n,\text{GINI}}-\overline{I_{\text{GINI}}}-\zeta_{\text{GINI}}\alpha_n\right)^2}{2\sigma^2_{I_{\text{GINI}}}}}\right). \tag{19}$$

We also count the number of ride-sourcing companies (i.e. TNC, including Uber/Lyft/Others) used in the past as another indicator, which is denoted as $I_{n,\text{TNC}}$ and can take any integer from 0 to 3. It suggests "no experience with ride-sourcing services", "one company", "two companies" and "more than two companies" if $I_{n,\text{TNC}}$ takes a value of 0, 1, 2 and 3, respectively.[3] The remaining two indicators are the responses to the two attitudinal statements described in section 2.5. As shown in Table 6, higher agreement towards these two statements is associated with a wider choice of alternatives in the SC survey, as well as higher frequency of choosing the new UberAIR alternative. We denote these two indicators as $I_{n,\text{ATTI8}}$ and $I_{n,\text{ATTI10}}$, accordingly.

We deal with $I_{n,\text{TNC}}$, $I_{n,\text{ATTI8}}$ and $I_{n,\text{ATTI10}}$ in a different way by accounting for the ordered characteristics of them, as omitting this nature would result in a lost of behavioural explanation power (Daly et al., 2012b; Dekker et al., 2016). Following Daly et al. (2012b), we specify an ordered logit model for each ordinal indicator. We denote L_c as the number of levels that indicator c can take, and use ζ_c to measure the impact of latent variety-seeking α_n on

[3] This indicator is created according to the 15 binary responses towards 15 different types of ride-sourcing services provided by Uber, Lyft and other companies, including both basic economic services and expensive premium services. If a respondent has not used any of the 15 types or claimed to "I don't know" about these ride-sourcing services, we assume they have no experience with ride-sourcing services.

the value of $I_{n,c}$. Thus, the probability of observing indicator $I_{n,c}$ taking the value of level l ($l \in (1, \cdots, L_c)$) for respondent n is written as:

$$P(I_{n,c} = l \mid \alpha_n) = \frac{e^{\mu_{c,l} - \zeta_c \alpha_n}}{1 + e^{\mu_{c,l} - \zeta_c \alpha_n}} - \frac{e^{\mu_{c,l-1} - \zeta_c \alpha_n}}{1 + e^{\mu_{c,l-1} - \zeta_c \alpha_n}}, \tag{20}$$

where $\mu_{c,l}$ is the threshold parameter for indicator c and level l. For normalisation purpose, we set $\mu_{c,0} = -\infty$ and $\mu_{c,L_c} = +\infty$, and each indicator only needs $L_c - 1$ thresholds to be estimated. As such, the likelihood of observing the responses towards the four indicators by respondent n given the value of α_n is written as:

$$P(I_n \mid \alpha_n) = P(I_{n,\text{GINI}} \mid \alpha_n) P(I_{n,\text{TNC}} \mid \alpha_n) P(I_{n,\text{ATTI8}} \mid \alpha_n) P(I_{n,\text{ATTI10}} \mid \alpha_n) \tag{21}$$

3.4.4 Log-likelihood function

Combining Eq. 16 and Eq. 21, the log-likelihood function of observing all the stated choices and the indicators across all the respondents can be obtained by taking the integral over all possible value of the random latent variable of α_n, such that:

$$\begin{aligned} & LL(y, I) \\ &= \sum_{n=1}^{N} \ln \int_{\alpha_n} \left(\sum_{s=1}^{S} \pi_{n,s} \prod_{t=1}^{T} \left(\sum_{q=1}^{2} \phi_{n,q} P\left(y_{nt} \mid \delta_{(s,q)}, \beta_{(s,q)}\right) \right) \right) P\left(I_n \mid \alpha_n\right) \\ & f(\pi_n, \phi_n \mid \alpha_n) \mathrm{d}\alpha_n. \end{aligned} \tag{22}$$

Since no closed-form expression can be obtained for the resulting LL function due to the integral over the random latent variable, we use simulated log-likelihood to approximate the true LL.

4 Estimation and results

Maximum likelihood estimation (MLE) was adopted for each model. All the models in this paper were estimated in R using the package Apollo (Hess and Palma, 2019). The estimation results are summarised in Table 7. Moving from left to right, the specification complexity increases and each new model uses the estimates of the previous model as starting values in estimation.

In each model, UberX was chosen as the base alternative with the corresponding ASC parameters (including δ_{uberx}, $\delta_{\text{uberx},1}$, $\delta_{\text{uberx},2}$, and Δ_{uberx}) fixed to 0 and not shown in Table 7. This is due to that UberX was shown to each respondent in each choice task, and that UberX has the lowest variance in the unidentified MMNL model that estimates the variance of all the alternatives (Walker et al., 2007). Before proceeding with a discussion of the estimation results in detail, it needs to be noted that as part of confidentiality agreement, the estimates (i.e. ASCs) from which the market shares could be inferred are not shown in Table 7, and the differences in individual preferences across alternatives are not discussed in this section. More precisely, δ_i in the MNL model, and $\delta_{i,1}$ for the first class in all the latent class models are hidden, marked with "$\star$". Meanwhile, instead of presenting the ASC parameters $\delta_{i,2}$ for the second class in each latent class model, we show how much the ASCs shift in the second class against the first class for the same alternative, together with the t-ratio statistics indicating the significance of the difference between classes. Nevertheless, a positive/negative difference in ASC for a same alternative does not necessarily imply a higher/lower market share for that alternative in Class 2 than Class 1 given the comparison is across all alternatives.

-For better illustration of the differences across models and across (sub)classes within each latent class model, we further conducted post-estimation analysis for each model, of which the results are presented in Table 8. To state more precisely:

- Firstly, we calculated value-of-time (VoT, \$/min) for each time component. The VoT estimates were calculated over the sample for the MNL model and were computed both over the sample and within each class for all the latent class models. As to model 3 and model 4, since only ASCs vary at the task-level whereas all the sensitivity parameters are kept constant across choice tasks within a class, VoT results are the same for a "with-intra" subclass and a "no-intra" subclass if they are grouped under a same class s at the inter-individual layer. It needs to be noted that as a non-linear specification of travel cost is adopted in each model, VoT depends on the travel cost. Herein, we used the price of the chosen alternative in calculating VoT estimates.

- Secondly, we computed the market share for each alternative by averaging the choice probabilities for each alternative across all the tasks using the model estimates. These market shares were obtained at the sample level for the MNL model, and were calculated within each class for the basic latent class model (i.e. model 2). Regarding the two-layer latent class models (i.e. model 3 and model 4), we can obtain four different sets of within-class choice probabilities, each for one subclass due to the fact that both ASCs and sensitivity parameters are involved in calculating utility functions for the alternatives. For the "with-intra" subclass, the choice probability for each alternative at a given choice task is obtained by averaging across all the 16 combinations.
  Again, due to confidentiality restrictions, we cannot present the detailed market shares across alternatives. Instead, we illustrate the order of market shares for the same alternative across (sub)classes. Specifically, we hide the market shares for the MNL model and for the first (sub)class in each latent class model (i.e. Class 1 in model 2, and subclass (1,1) in model 3 and model 4), marked with "$\star$". For each latent class model, we indicate how the market share in each of the remaining (sub)classes changes relative

to the first (sub)class for a given alternative. The minus symbol "−" and the plus symbol "+" suggest that the market share in the corresponding (sub)class is lower and higher than that in the starred first (sub)class, respectively. When there are more than two classes, and using the example where the value is highest in the first class, a single − indicates the second highest value for that ASC, a double −− the third highest, etc.

4.1 Model 1: MNL model

As shown in Table 7, people are found to present almost twice as strong a sensitivity towards egress time (est.=-0.033, rob.t=-4.28) than towards the other three types of time components. A delta method calculation suggests the other three time components are not significantly different from each other in values (Daly et al., 2012a).

The differences in marginal utilities of different time components can also be revealed by the VoT estimates in Table 8. Egress time has the highest value, with \$35.97/h for the whole sample.

4.2 Model 2: Basic LC model

The second model is a basic latent class model, where preference heterogeneity is accommodated solely across respondents.

4.2.1 Sample-level results

Comparing with model 1, the value of access time and flight time over the sample are both higher in model 2. Egress time has the highest VoT over the sample in both model 1 and model 2, and is relatively consistent in all four models, indicating that the convenience of moving from landing pads to final destinations plays a crucial role in determining the attractiveness of UberAIR. This implies the significance of integrating and coordinating the existing ground-based services with UberAIR.

4.2.2 Class-specific results

Compared to model 1, model 2 illustrated preference heterogeneity across respondents. As shown in Table 7, the constant γ_1 (est.=0.280, rob.t=3.78) in the class allocation function implies a probability of 56.95% for respondents to fall into Class 1 and a probability of 43.05% to be in Class 2. Comparing the model estimates of the two classes, it can be found that Class 2 is associated with significantly lower sensitivities towards all the attributes, including travel cost.

If further looking at the VoT results in Table 8, we can see that Class 2 shows much lower VoT for all the time components, except for in-vehicle time

δ_{uberair}	⋆	⋆	$\delta_{\text{uberair},1}$	⋆	⋆	$\delta_{\text{uberair},1}$	⋆	⋆	$\delta_{\text{uberair},1}$	⋆	⋆
			$\beta_{\text{access},2}$	-0.018	-2.56	$\beta_{\text{access},2}$	-0.061	-5.08	$\beta_{\text{access},2}$	-0.062	-5.04
			$\beta_{\text{egress},2}$	-0.044	-5.57	$\beta_{\text{egress},2}$	-0.088	-5.24	$\beta_{\text{egress},2}$	-0.091	-5.10
			$\beta_{\text{flight},2}$	-0.021	-4.87	$\beta_{\text{flight},2}$	-0.044	-5.29	$\beta_{\text{flight},2}$	-0.046	-5.19
			$\beta_{\text{invehi},2}$	-0.021	-8.37	$\beta_{\text{invehi},2}$	-0.044	-10.62	$\beta_{\text{invehi},2}$	-0.045	-10.34
			$\beta_{\text{cost},2}$	-1.740	-15.93	$\beta_{\text{cost},2}$	-3.156	-16.75	$\beta_{\text{cost},2}$	-3.185	-16.55
			$\delta_{\text{car},2} - \delta_{\text{car},1}$	2.499	2.40	$\delta_{\text{car},2} - \delta_{\text{car},1}$	4.072	3.11	$\delta_{\text{car},2} - \delta_{\text{car},1}$	4.030	3.04
			$\delta_{\text{transit},2} - \delta_{\text{transit},1}$	-7.148	-5.96	$\delta_{\text{transit},2} - \delta_{\text{transit},1}$	-14.826	-6.22	$\delta_{\text{transit},2} - \delta_{\text{transit},1}$	-14.597	-6.16
			$\delta_{\text{uberpool},2} - \delta_{\text{uberpool},1}$	3.348	19.07	$\delta_{\text{uberpool},2} - \delta_{\text{uberpool},1}$	4.768	16.20	$\delta_{\text{uberpool},2} - \delta_{\text{uberpool},1}$	4.868	16.40
			$\delta_{\text{uberair},2} - \delta_{\text{uberair},1}$	-1.017	-3.31	$\delta_{\text{uberair},2} - \delta_{\text{uberair},1}$	-3.600	-6.86	$\delta_{\text{uberair},2} - \delta_{\text{uberair},1}$	-3.545	-6.66
			γ_1	0.280	3.78	γ_1	0.452	6.54	γ_1	0.444	5.95
			-			-	-	-	τ_{NS}	-0.523	-9.24
						Δ_{car}	3.315	10.00	Δ_{car}	3.332	9.81
						Δ_{transit}	11.205	9.45	Δ_{transit}	11.244	9.32
						Δ_{uberpool}	-5.008	-10.25	Δ_{uberpool}	-5.037	-10.07
						Δ_{uberair}	8.761	23.35	Δ_{uberair}	8.851	22.97
						λ_1	0.738	11.49	λ_1	0.798	11.61
						-	-	-	τ_{AT}	-0.325	-5.27
									ζ_{ATTI8}	1.616	12.78
									ζ_{ATTI10}	1.555	12.69
									ζ_{GINI}	-0.068	-13.17
									ζ_{TNC}	1.111	12.64
									σ_{GINI}	0.206	75.22
									$\mu_{\text{ATTI8\_1}}$	-3.250	-22.72
									$\mu_{\text{ATTI8\_2}}$	-1.145	-14.42
									$\mu_{\text{ATTI8\_3}}$	0.794	12.10
									$\mu_{\text{ATTI8\_4}}$	3.004	22.58
									$\mu_{\text{ATTI10\_1}}$	-3.500	-23.46
									$\mu_{\text{ATTI10\_2}}$	-2.246	-21.05
									$\mu_{\text{ATTI10\_3}}$	0.121	2.01
									$\mu_{\text{ATTI10\_4}}$	1.991	20.71
									$\mu_{\text{TNC\_noexperience}}$	-0.850	-16.18
									$\mu_{\text{TNC\_one}}$	0.671	11.82
									$\mu_{\text{TNC\_two}}$	5.226	22.10
									κ_{age}	-1.185	-12.87
									κ_{income}	0.213	10.16
									κ_{female}	-0.660	-11.23
									κ_{delay}	0.200	3.79
									κ_{vehicles}	-0.094	-3.36

Table 8 Value-of-time estimates and choice probabilities

		model 1: MNL	model 2: basic LC			model 3: 2L-LC					model 4: 2L-LV-LC				
parameter #		9	19			24					47				
$LL(whole)$		-20740.78	-16929.74			-15625.74					-24443.96				
$LL(SC)$											-15613.48				
ρ^2		0.3398	0.4611			0.5026					SC component: 0.5030				
BIC		41572.4	34051.26			31493.73					whole model: 49362.33				
		All	**Class 1 (avoid novelty)**	**Class 2 (seek novelty)**	**All**	**Class 1 (avoid novelty)**		**Class 2 (seek novelty)**		**All**	**Class 1 (avoid novelty)**		**Class 2 (seek novelty)**		**All**
Value of time (VoT, $/h)	access time	15.07	36.20	13.43	26.40	27.05		24.74		26.15	26.66		25.07		26.03
	egress time	35.97	44.77	32.28	39.40	32.93		36.14		34.18	32.89		36.78		34.43
	flight time	14.27	28.36	15.32	22.75	22.57		18.11		20.83	22.22		18.53		20.75
	invehicle time	19.19	14.51	15.87	15.09	11.30		18.14		13.96	11.15		18.16		13.94
						no-intra subclass (1,1)	**with-intra subclass (1,2)**	**no-intra subclass (2,1)**	**with-intra subclass (2,2)**		**no-intra subclass (1,1)**	**with-intra subclass (1,2)**	**no-intra subclass (2,1)**	**with-intra subclass (2,2)**	
Market share changes	car	⋆	⋆	-		⋆	-	- -	- - -		⋆	-	- -	- - -	
	transit	⋆	⋆	-		⋆	-	- - -	- -		⋆	-	- - -	- -	
	UberX	⋆	⋆	-		⋆	- - -	-	- -		⋆	- - -	-	- -	
	UberPool	⋆	⋆	+		⋆	+	+++	++		⋆	+	+++	++	
	UberAir	⋆	⋆	+		⋆	++	+	+++		⋆	++	+	+++	

which is almost similar between classes. Overall, Class 1 exhibits higher VoT than Class 2 in model 2.

The distinction in preferences towards different alternatives across classes can be manifested by the within-class choice probability of each alternative. As shown in Table 8, Class 2 shows higher probability to select the UberPOOL and UberAIR options than Class 1, whereas car, transit and UberX all have lower proportions in Class 2 than Class 1. Since UberPOOL was unavailable in reality in the Dallas area during the data collection period, the UberPOOL alternative can also be seen as a new mode for respondents approached there. In this sense, we can infer from model 2 that Class 2 individuals are more likely to try new service(s) than Class 1 individuals.

4.3 Model 3: 2L-LC model

Model 3 accounts for intra-individual preference heterogeneity in addition to inter-individual preference heterogeneity, resulting in four subclasses in total. The findings with respect to the VoT and choice probabilities over the sample in model 3 do not present much differences against model 2. However, model 3 can give more insight on preference patterns and market segmentation (see section 4.3.4).

4.3.1 Model estimates

We first look at the sensitivity parameters at the inter layer in Table 7. Similarly to model 2, marginal utilities for most of the attributes in Class 2 (same values for subclass $(2, 1)$ and subclass $(2, 2)$) are significantly lower than the corresponding parameters in Class 1 (same values for subclass $(1, 1)$ and subclass $(1, 2)$). The only exception is in-vehicle time, of which the difference is insignificant between classes (diff.=-0.014, rob.t=-1.51, by delta method calculation).

Turning to the model estimates at the intra layer, the significant estimates of the shift terms $\varDelta$ for all the ASCs suggest that the two-layer LC models can successfully detect the variation and instability of preference over choice tasks for a given respondent. Compared to the base alternative UberX, people's preferences towards transit and UberAIR are much more unstable across choice tasks, whereas the preference disturbance with respect to car and UberPOOL is relatively milder.

The two class allocation models are both solely explained by a constant. Parameter γ_1 (est.=0.452, rob.t=6.54) results in a generic probability to fall into either Class 1 (i.e. 61.11%) or Class 2 (i.e. 38.89%) across respondents. Parameter λ_1 (est.=0.738, rob.t=11.49) leads to a generic probability of 67.66% in belonging to a "no-intra" subclass and 32.34% in being assigned to a "with-intra" subclass.

4.3.2 Value-of-time results

Regarding the VoT patterns shown in Table 8, Class 1 respondents present higher value of access time and flight time, but lower value for egress time from landing pads and time spent in vehicles on land, compared to Class 2 respondents. It appears that we cannot, like in model 2, detect clearly distinctive patterns between classes in model 3 (and also in model 4) which accounts for the instability of preferences towards alternatives across choice tasks according to the VoT results.

4.3.3 Within-class choice probabilities

Nevertheless, the within-class choice probabilities for different alternatives can provide sufficient indications with respect to the characteristics of each class. Similar to the results of model 2, we can see that Class 2 respondents (including both subclass $(2,1)$ and subclass $(2,2)$) present higher probabilities to adopt the new UberAIR alternative as well as the UberPOOL alternative, while Class 1 respondents (including both subclass $(1,1)$ and subclass $(1,2)$) are much more prone to stick to the other existing ground-based modes, particularly personal/household vehicle and transit. These results imply that Class 2 individuals are more likely to try the new service(s) than Class 1 individuals.

Furthermore, in order to illustrate the differences between "no-intra" and "with-intra" subclasses under a same set of sensitivities, we calculate the mean of chosen probability for each subclass which is averaged over all the observations. It is found that the "no-intra" subclasses $(1,1)$ and $(2,1)$ have higher average chosen probabilities (i.e. 66.04% and 55.88%) than "with-intra" subclasses $(1,2)$ and $(2,2)$ (i.e. 45.85% and 30.30%), respectively. This suggests that respondents who fall into the "with-intra" class are associated with less deterministic choices, which is in accordance with our expectation.

4.3.4 Classes' profiles

Combining the discussions above, we can obtain the profiles as well as the allocation probabilities for all the four different subclasses of respondents as:

- Subclass $(1,1)$: 41.35%
  - Low tendency to try new modes including UberAIR (i.e. avoid novelty)
  - Stable preference across choice tasks (i.e. avoid alternation)
- Subclass $(1,2)$: 19.77%
  - Low tendency to try new modes including UberAIR (i.e. avoid novelty)
  - Unstable preference across choice tasks (i.e. seek alternation)
- Subclass $(2,1)$: 26.31%
  - High tendency to try new modes including UberAIR (i.e. seek novelty)
  - Stable preference across choice tasks (i.e. avoid alternation)
- Subclass $(2,2)$: 12.58%
  - High tendency to try new modes including UberAIR (i.e. seek novelty)
  - Unstable preference across choice tasks (i.e. seek alternation)

4.4 Model 4: 2L-LV-LC model

As a final step, we report the results of model 4 which uses latent variety-seeking as an additional explanatory variable in explaining class allocation probabilities across the individuals. Overall, model 4 presents very similar patterns to model 3, in terms of model estimates, VoT results and within-class choice probabilities. Herein, we only discuss the unique characteristics of model 4, i.e. the impact of latent variety-seeking.

4.4.1 Variety-seeking in class allocation models

As shown in Table 7, the constants γ_1 and λ_1 at the inter-individual layer are very close to those in model 3. The negative and significant τ_{NS} (est.=-0.523, rob.t=-9.24) means that a higher value of the latent variable α would result in greater propensity to fall into Class 2, which features stronger willingness to choose the new UberAIR service. Similarly, the negative and significant τ_{AT} (est.=-0.325, rob.t=-5.27) implies a decrease in probability of belonging to "no-intra" subclasses $(1,1)$ and $(2,1)$ with an increase in the latent variable α. Thus, the probabilities of falling in a given subclass vary across respondents in model 4, depending on the value of α.

4.4.2 Variety-seeking in measurement model component

Now we jointly examine the role of the latent variable α in the class allocation functions and in the measurement equations. The threshold parameter $\mu_{c,l}$ presents a monotonically increasing trend as the level l goes up for each ordinal indicator c. From the positive and significant parameters ζ_{ATTI8}, ζ_{ATTI10} and ζ_{TNC}, we can see that an increase in the latent variable α would lead to a stronger agreement towards the attitudinal statements ATTI8 and ATTI10, as well as a larger number of ride-sourcing companies experienced in the past. In terms of the "Gini" coefficient, the negative and significant ζ_{GINI} implies that a stronger α is associated with a lower Gini coefficient, suggesting less inequality and less uniqueness in mode choice experience. All these contribute to the inference that the latent variable α can indeed be interpreted as "variety-seeking", such that a larger value in α corresponds to stronger variety-seeking.

Combining the interpretation of the latent variable α and the class allocation models, our hypothesis can be confirmed. We can reach the conclusion that variety-seeking plays a role in both the inter-individual preference heterogeneity and the intra-individual preference heterogeneity. Specifically, compared to variety avoiders, variety seekers are more likely to fall into the class with higher probabilities to switch to the novel UberAIR and UberPOOL options, and lower probabilities to choose the long-existing car and transit alternatives. This is in line with an earlier study of variety-seeking in the context of intermodality between air and high-speed rail, where variety seekers are found to be more likely to select the new integrated HSR-air alternative (Song et al., 2018), as well as another study in the context of ride-sourcing services, where variety-seekers are found to be more inclined to use ride-sourcing services (Alemi et al., 2018). Additionally, we discovered that variety seekers also have higher propensity to belong to the "with intra" subclasses, where preferences across choice tasks are unstable and less deterministic. This implies that in the course of completing a SC survey, variety-seekers are more likely to switch their mode choices among different alternatives continuously.

Consequently, the classification of respondents and profiles of different subclasses discussed in section 4.3.4 can be retrieved by model 4. Notably, due to the significant role of latent variety-seeking, the probability of falling into each of the four subclasses varies across respondents rather than being generic.

4.4.3 Structural equation for variety-seeking

After regressing the responses towards attitudinal statements related to variety-seeking on different socio-demographic and trip characteristics, we adopt *age*, *income*, *the number of owned vehicles*, *gender* and *whether experienced delay* as explanatory variables in the final specification for Eq. 13. All these covariates are centred on 0, so that the latent variable has a mean of 0. Age, income and the number of owned vehicles are treated as continuous variables, while the remaining two variables are treated as binary ones. To avoid incomparable scales between different covariates, we divide the age and income variables by the original mean values.

Parameters κ in Table 7 show how these explanatory variables affect the value of latent variety-seeking. As expected, the negative κ_{age}, κ_{female} and κ_{vehicles} show that older people, female respondents and people with more vehicles are characterised by weaker variety-seeking tendency, whereas the positive κ_{income} and κ_{delay} suggest that people with more income and who have experienced delay on the same trip in the past have a stronger variety-seeking tendency.

4.5 Comparisons of model fit

Moving from model 1 to model 2 and then model 3, we can see that model fit improves as the model specification becomes more complex, in terms of the log-likelihood, ρ^2 values and the Bayesian Information Criterion (BIC). This improvement over models can also be confirmed by the likelihood ratio test, of which the p-value is 0 when comparing model 2 against model 1, and comparing model 3 against model 2. All these reflect the significant benefits obtained from better accommodation of preference heterogeneity, both across individuals and within individuals.

Obviously, it is reasonable to see that both log-likelihood and BIC for the whole model in model 4 are much worse than in other simpler models, as model 4 simultaneously explains the observations of indicators of latent variety-seeking in the measurement model component. We acknowledge that Vij and Walker (2016) have demonstrated that incorporating latent variables in the choice model cannot result in better fit than a corresponding reduced form model without latent variables. In the present paper, neither explanatory variables nor random terms are incorporated in the allocation functions in model 3, meaning that model 3 does not have the same flexibility as model 4 does. Thus, it is reasonable to achieve a slight improvement in fit for the choice component in model 4.

5 Conclusions

Shared mobility is becoming prevalent in many large cities around the world. It encompasses diverse ground-based sharing services, and is now reaching out to the next dimension for shared air travel, i.e. Ubran Air Mobility, which is expected to be facilitated by on-demand vertical take-off-and-landing (VTOL) aerial vehicles. However, empirical analyses on mode choice behaviour and travel demand when the new air taxi service joins the big family of shared mobility remain very limited.

This paper was generated based on the assumption that when a novel travel mode/service enters the market, an underlying construct of variety-seeking would play a role in affecting people's preference patterns and choice behaviour. Existing psychological studies on variety-seeking have discovered that a greater tendency to seek variety can be associated with stronger inclination towards something novel or unfamiliar, and (or) with more fluctuating preferences towards different alternatives. Hence, we also distinguished between these two aspects of variety-seeking in this paper. Specifically, we associated the novelty-seeking aspect with inter-individual preference heterogeneity and relate the alternation aspect with intra-individual preference heterogeneity.

As the novel on-demand VTOL air taxi has not yet been put into commercialised operation, this paper made use of stated choice data provided by Uber on mode choice amongst different conventional modes and different shared mobility services, including its upcoming air taxi service called UberAIR.

The key contribution of this paper lies in the approach we adopted to account for the impact of variety-seeking. We established a new latent class model with two layers of preference heterogeneity, where variety-seeking was treated as a latent variable. At the inter-individual layer, respondents were first segmented into two classes, one of which exhibiting higher propensity to adopt the new UberAIR service than the other. Each class was further segmented into two subclasses - one subclass with consistent and stable preferences throughout choice tasks and another subclass with preference variation across choice tasks. Each step of segmentation was a function of the latent variable of variety-seeking, such that the role of the novelty-seeking aspect and alternation aspect can be captured separately. Intra-individual preference heterogeneity was accommodated for the "with-intra" subclasses to control for the alternation aspect of variety-seeking through an additional layer of discrete mixture over 16 different combinations of values, where ASCs of the alternatives varied. That is, this model replaced continuous distributions used in the conventional approach of accommodating inter-and-intra individual preference heterogeneity (Hess and Rose, 2009) with discrete distributions at both layers, which can massively reduce computational burden.

The model detected significant and expected impact of variety-seeking in each class allocation function, suggesting that in our case variety-seeking tendencies result in both novelty-seeking and alternation behaviour. That is, variety-seekers are not only more likely to switch to the new UberAIR alternative, but also more likely to have unstable preference towards various alternatives across choice tasks in the SC survey than variety-avoiders. It is discovered that people with higher income and those with delay experience on the same trip in the past have stronger variety-seeking tendencies. In the meantime, those variety-seekers were also observed to show stronger agreement in attitudinal statements describing their interest in adopting new technologies. They were also found to be associated with wider exposure of ride-sourcing services and other types of ground-based transport modes in the past. The modelling results also provided more empirical evidence of the presence of intra-individual preference heterogeneity (on top of inter-individual preference heterogeneity) and suggested that only a segment of respondents have such preference variation across choice tasks (due to alternation effect) while others are found to be more consistent in preferences in the SC survey.

We acknowledge the shortcomings of the proposed two-layer latent class framework. This mainly relates to the estimation method we used, i.e. maximum log-likelihood estimation. Thus a model built within this framework might struggle with local optimum issue and the estimation results could be very sensitive to the starting values. We have tried to minimise the impact of these issues by using the estimates of a more constrained model as the starting values of a more general model with more complex specification. Nevertheless, it would be worth testing the model with other alternative estimation methods, e.g. EM algorithms (Train, 2008).

We believe that the work conducted in this study is relevant not just to a transport setting but to the many other consumer scenarios where new options are introduced to the market. Future research potentials include replicating this work in other choice contexts and test the performance of this new two-layer latent class model with (or without) latent variables in explaining inter and intra individual preference heterogeneity. Of course, a two-layer latent class model can have more than two classes at each level, such that it could be tailored to meet the requirement of a specific study. Finally, it is also worth exploring if variety-seeking is driven by novelty-seeking, whether seeking novelty is a purely short-term effect, or also works in the longer run as a counterpart to habits and thereby justifies the existence of a competitive market with alternative options to select from, e.g. examine adoption and diffusion of new technology (El Zarwi et al., 2017).

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