

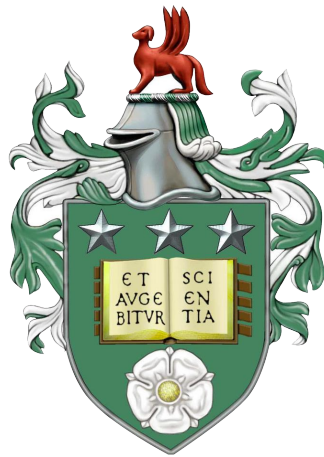
---

---

# Understanding mode choice behaviour when new modes come into play

---

---



Submitted in accordance with the requirements  
for the degree of Doctor of Philosophy  
by  
Fangqing Song

University of Leeds  
Institute for Transport Studies  
September 2019



# Intellectual property and publications

The candidate confirms that the work submitted is her own, except where work which has formed part of jointly authored publications has been included. The contribution of the candidate and the other authors to this work has been explicitly indicated below. The candidate confirms that appropriate credit has been given within the thesis where reference has been made to the work of others.

The work in Chapter 2 has been published as follows:

**Song, F.**, Hess, S., Dekker, T., (2018). *Accounting for the impact of variety-seeking: theory and application to HSR-air intermodality in China*. *Journal of Air Transport Management*, 69, 99-111.

The candidate developed the main idea for this paper and designed the survey under the guidance of Stephane Hess and Thijs Dekker. The candidate collected the data, performed the data analysis, conducted the modelling work and wrote the manuscript. Stephane Hess and Thijs Dekker provided recommendations on the modelling and comments on the results. The manuscript was improved by comments from all the co-authors.

The work in Chapter 3 has been submitted to *Transportation* and is under review:

**Song, F.**, Hess, S., Dekker, T., (under review). *Fancy commuting by air taxi? Uncovering the impact of variety seeking on the demand for new shared mobility services*.

The main idea for this work was developed by the candidate under the guidance of Stephane Hess and Thijs Dekker. The candidate performed data analysis, conducted the modelling work and wrote the manuscript. Stephane Hess and Thijs Dekker contributed to the idea, provided recommendations on the modelling work and comments on the results. The manuscript was improved by

comments from all the co-authors.

The work in Chapter 4 has been submitted to *Transportmetrica A: Transportation Science*, and the candidate has received an invitation for re-submission after revising the manuscript:

**Song, F.**, Hess, S., Dekker, T., (under revision). *A joint model for stated choice and best-worst scaling data using latent attitude importance: application to high speed rail.*

The candidate developed the main idea for this work and designed the survey under the guidance of Stephane Hess and Thijs Dekker. The candidate collected the data, performed the data analysis, conducted the modelling work and wrote the manuscript. Stephane Hess and Thijs Dekker contributed to the idea, provided recommendations on the modelling work and comments on the results. The manuscript was improved by all the co-authors.

This copy has been supplied on the understanding that it is copyright material and that no quotation from the thesis may be published without proper acknowledgement.

©2019 The University of Leeds and Fangqing Song

The right of Fangqing Song to be identified as Author of this work has been asserted by her in accordance with the Copyright, Designs and Patents Act 1988.

# Acknowledgements

I would like to express my highest and sincere gratitude to my supervisors Prof. Stephane Hess and Dr Thijs Dekker for their consistently generous support and guidance as well as unimaginable abundance of patience and encouragement. They have set outstanding role models, inspiring me to overcome fears and difficulty I have met in this journey. I am also very grateful that my supervisors have helped me with expanding network, promoting academic research and seeking professional opportunities.

This PhD research would not have been possible without the funding offered by China Scholarship Council (CSC). I am extremely grateful to CSC for giving me this valuable opportunity. I would also like to thank the research funding provided by Research Training Support Grant (RTSG) and Leeds*for*Life for supporting me to attend a number of academic conferences.

Part of my PhD research made use of data provided by Uber Technologies, Inc (“Uber”). Neither the University of Leeds nor the authors received funding or financial support from Uber. I am very thankful that Uber granted us access to using the data for research purposes and encouraged us to disseminate research findings at academic conferences.

This thesis benefited substantially from the High Performance Computing (HPC) resource at University of Leeds, without which this research would not have been completed in time. Thanks also go to my friend Jinfang Wang, who helped me with cloud computing before I started using HPC.

I am sincerely grateful for the insightful comments from and useful discussions with my PhD examiners Dr Charisma Choudhury and Dr Dimitris Potoglou. My heartfelt thanks also go to all the staff and PhD students at the Institute for Transport Studies (ITS), especially my fellow members in Choice Modelling Centre, for them having created such wonderful environment to exchange ideas and stimulate self-development. I especially owe a big thank-you to Chiara Calastri, Mauro Capurso, David Palma and Hongbo Ye who have been very supportive and patient when I ask questions or need help.

I would like to thank Jie Ma for encouraging me to chase my dream during the last year of my Masters when I needed to decide whether to pursue a PhD.

## Acknowledgements

Special thanks go to Jeff Tjong, who has made my four years in Leeds even more memorable and precious. Most of all, I would like to thank my parents for always standing by my side and for their unconditional love and support.

# Abstract

Smart mobility has become increasingly prevalent nowadays, and new travel modes have been emerging in this process. The entry of these new modes not only fosters diversity of transport systems, but also would lead to changes of the characteristics of the transport system itself. This may induce changes in individual travel behaviour. For example, some people would shift to a new mode from other existing modes, while other individuals might be induced to make additional travel which would not be made if the new mode is not available. Some unique underlying characteristics may also drive these changes in travel behaviour. For instance, while some individuals are resistant to change, others may be prone to adopt novel options. This necessitates the investigation of the impact of variety-seeking on how people make choices when new modes are involved. Secondly, while choices are relatively stable for some individuals, others may have stronger tendencies to vary their choices more frequently over choice occasions. Exploration into this characteristic is needed to facilitate better understanding of people's consecutive choices over time. Thirdly, a new mode is usually associated with some new attributes with which individuals may be less familiar. This entails obtaining more knowledge of the role that attributes play in choice making for travel behaviour researchers. This thesis aims at examining mode choice behaviour at an individual level and uncovering travel demand through empirical analyses. Contributions are made to accounting for the three unique underlying characteristics in behaviour as mentioned above, which enhance understanding of the determinants behind mode choices and heterogeneity in preferences in the context of the introduction of new modes. This thesis exclusively uses stated preference (SP) data, as SP data can be used for preference elicitation in hypothetical scenarios, whereas it is much more difficult to collect revealed preference data when new modes have not yet been launched or have only existed in the market for a short period. This research relies on discrete choice modelling (DCM), which is a well-established econometric method for analysing individual choice behaviour and aggregate demand. DCM enables the accommodation of complex heterogeneity in preferences both across individuals and within individuals, and to achieve greater behavioural re-

alism in delineating decision-making. The integrated choice and latent variable (ICLV) model is adopted in different manners, illustrating that the incorporation of latent variables is not confined to investigating the impact of unobserved psychological factors (e.g. variety-seeking) in choices or in class allocation, but could be extended for the purpose of combining stated choice (SC) data with other alternative SP data, e.g. best-worst scaling (BWS) data. The research findings are as expected. The study in the context of HSR (high-speed rail)-air intermodality suggests that people with stronger variety-seeking tendencies are more likely to adopt the new mode introduced. The same finding has been discovered in the second study that applies to the context where a hypothetical air taxi service is involved, which further shows that stronger variety-seeking tendencies can also lead to more unstable preferences across choices. The third study that synthesises traditional SC data and additional BWS data demonstrates the correlation between these different types of collection methods, illustrates that attributes play a relatively consistent - though not one-to-one - role across different methods, and enables the exploration of behavioural information per individual to a greater extent. In general, this thesis contributes to deeper understanding of mode choice behaviour in the context of the introduction of new modes. That is, the investigation into the impact of various level-of-service attributes provides empirical evidence for transport practitioners in willingness-to-pay evaluation. Moreover, the research indicates that while variety-seekers are more likely to be attracted to adopt a new mode at an early stage, they might in the meantime have less consistency in using the new mode. Thus, policy makers could expect an initial uptake of the new mode in the population, but it does not necessarily mean that people would keep on using the new mode over time. Furthermore, this research shows that when confronting the introduction of a new mode characterised with new attributes, an applicable approach for policy makers to improve the understanding of trade-offs and forecast of travel demand would be jointly using alternative preference elicitation methods together with the traditional SC survey.



# Contents

<b>Intellectual property and publications</b>	<b>iii</b>
<b>Acknowledgements</b>	<b>v</b>
<b>Abstract</b>	<b>vii</b>
List of Tables . . . . .	xiii
List of Figures . . . . .	xv
<b>Abbreviations</b>	<b>xvii</b>
<b>1 General introduction</b>	<b>1</b>
1.1 Context . . . . .	1
1.2 Related work . . . . .	5
1.2.1 Transport background . . . . .	6
1.2.2 Behavioural underpinning . . . . .	12
1.2.3 Preference elicitation methods . . . . .	16
1.2.4 Representation of preference heterogeneity . . . . .	18
1.3 Research gaps . . . . .	22
1.4 Data used in this thesis . . . . .	24
1.5 Objectives and implementation . . . . .	26
1.6 Thesis outline and contributions . . . . .	28
References . . . . .	31
<b>2 Accounting for the impact of variety-seeking: theory and application to HSR-air intermodality in China</b>	<b>41</b>
2.1 Introduction . . . . .	42
2.1.1 Research background . . . . .	42
2.1.2 Research questions . . . . .	43
2.2 Literature review and research contribution . . . . .	44
2.2.1 HSR-air intermodality analysis . . . . .	44
2.2.2 Variety-seeking analysis . . . . .	46
2.2.3 Research contribution . . . . .	47

2.3	Data . . . . .	48
2.3.1	Regional context . . . . .	48
2.3.2	Definition . . . . .	49
2.3.3	Questionnaire and respondent sampling . . . . .	50
2.3.4	Stated choice component . . . . .	51
2.3.5	Attitudinal statements . . . . .	57
2.4	Methodology . . . . .	59
2.4.1	Multinomial logit model (MNL) . . . . .	59
2.4.2	Mixed multinomial logit model (MMNL) . . . . .	59
2.4.3	Integrated choice and latent variable model (ICLV) . . . . .	60
2.5	Empirical analysis . . . . .	63
2.5.1	Model specification . . . . .	63
2.5.2	Estimation results . . . . .	64
2.6	Discussions and conclusions . . . . .	71
	References . . . . .	75
<b>3</b>	<b>Fancy sharing an air taxi? Uncovering the impact of variety seeking on the demand for new shared mobility services</b>	<b>81</b>
3.1	Introduction . . . . .	82
3.1.1	Research background . . . . .	82
3.1.2	Motivations and objectives . . . . .	84
3.2	Survey and data . . . . .	86
3.2.1	UberAIR service context . . . . .	86
3.2.2	Questionnaire and respondent sampling . . . . .	86
3.2.3	Trip experience and socio-demographic characteristics . . . . .	89
3.2.4	Stated choice survey . . . . .	90
3.2.5	Attitudinal statements . . . . .	92
3.3	Methodology . . . . .	95
3.3.1	Multinomial Logit (MNL) model . . . . .	96
3.3.2	Basic Latent Class (LC) model . . . . .	96
3.3.3	Two-layer Latent Class (2L-LC) model . . . . .	97
3.3.4	Two-layer Latent Variable Latent Class (2L-LV-LC) model . . . . .	101
3.4	Estimation and results . . . . .	105
3.4.1	Model 1: MNL model . . . . .	110
3.4.2	Model 2: Basic LC model . . . . .	110
3.4.3	Model 3: 2L-LC model . . . . .	111
3.4.4	Model 4: 2L-LV-LC model . . . . .	113
3.4.5	Comparisons of model fit . . . . .	116
3.5	Conclusions . . . . .	116

References . . . . .	121
<b>4 A joint model for stated choice and best worst scaling data using latent attribute importance: application to high-speed rail</b>	<b>127</b>
4.1 Introduction . . . . .	128
4.2 Methodology . . . . .	131
4.2.1 Model framework . . . . .	131
4.2.2 Structural equations for latent variables . . . . .	132
4.2.3 Choice model . . . . .	133
4.2.4 Measurement models . . . . .	134
4.2.5 Log-likelihood . . . . .	137
4.2.6 Hypothesis . . . . .	137
4.3 Case study: Survey and data . . . . .	138
4.3.1 Survey background . . . . .	138
4.3.2 SC tasks . . . . .	139
4.3.3 BWS Case 1 tasks . . . . .	140
4.3.4 BWS Case 2 tasks . . . . .	142
4.4 Case study: Model estimation . . . . .	145
4.4.1 Model specification . . . . .	145
4.4.2 Estimation results . . . . .	148
4.5 Conclusions . . . . .	154
References . . . . .	158
<b>5 Discussions and conclusions</b>	<b>163</b>
5.1 Summary . . . . .	163
5.2 Accomplishment of objectives . . . . .	163
5.3 Contributions . . . . .	168
5.3.1 Practice . . . . .	168
5.3.2 Methodology . . . . .	170
5.4 Future research avenues . . . . .	173
<b>A Appendix to Chapter 2</b>	<b>177</b>
A.1 Screening criteria . . . . .	177
A.2 Identification of attributes . . . . .	177
A.2.1 Step 1: Literature review . . . . .	177
A.2.2 Step 2: Preliminary BWS survey . . . . .	178
A.2.3 Step 3: Pilot SC survey . . . . .	180
A.3 Experimental design for formal SC survey . . . . .	182
A.4 An example of questionnaire in the formal survey . . . . .	189

<b>B Appendix to Chapter 4</b>	<b>197</b>
B.1 Experimental design for the BWS case 1 survey . . . . .	197
B.2 Initial analyses for the TRB paper . . . . .	197
B.2.1 Analysis I: descriptive comparison between B-W scores and choice behaviour . . . . .	199
B.2.2 Analysis II: posteriors from Bayesian estimation . . . . .	200
B.2.3 Analysis III: hybrid choice model approach . . . . .	202

## List of Tables

1.1	Attributes considered in mode choice analyses in the context of air-HSR intermodality . . . . .	9
1.2	Data used in this thesis . . . . .	25
2.1	Descriptive statistics of the sample that completed the whole questionnaire . . . . .	52
2.2	Summary of experimental designs for formal SC survey . . . . .	56
2.3	Attitudinal statements on variety-seeking . . . . .	56
2.4	Model estimation results (choice model component and structural equations) . . . . .	65
2.5	Value of time calculations . . . . .	66
2.6	Estimation results of the measurement equations of the ICLV model	70
2.7	Sources of random taste heterogeneity . . . . .	70
3.1	Reference trips of sampled respondents . . . . .	88
3.2	Descriptive summary of reference trip experience within the focus sample (total amount: 2419) . . . . .	90
3.3	Descriptive summary of the focus sample . . . . .	91
3.4	Summary of stated choice tasks . . . . .	92
3.5	Attitudinal statements used for factor analysis. . . . .	93
3.6	Relation between the response of attitudinal statements and mode choice experience/ stated choices . . . . .	94
3.7	Estimation results of choice model and class allocation models . .	107
3.7	Estimation results of choice model and class allocation models (continued) . . . . .	108
3.8	Value-of-time (VoT) estimates and choice probabilities . . . . .	109
4.1	Average simple B-W scores and standard deviation for BWS1 data	142
4.2	Summary of the attribute levels in BWS2 tasks . . . . .	144
4.3	Analytical B-W scores for BWS2 data at the sample level . . . . .	145
4.4	Estimates for the reduced form MMNL model and the choice model component of the ICLV model . . . . .	149
4.5	Estimates of the MaxDiff measurement models on the BWS1 and BWS2 data . . . . .	150
4.6	Estimates in the structural equations and impact factors of latent attribute importance in the choice model and the BWS1/2 MaxDiff measurement models . . . . .	152

List of Tables

4.7	WTP estimates of the joint ICLV model and the reduced form MMNL model. . . . .	153
5.1	Accomplishment of objectives . . . . .	164
A.1	Simple best-minus-worst scores at the sample level . . . . .	180
A.2	Correlation matrix for BWS data . . . . .	181
A.3	Initial MNL estimates using data of the pilot SC survey and priors used in the design for the formal SC survey . . . . .	183
A.4	Experimental design for SC survey 1 . . . . .	185
A.4	Experimental design for SC survey 1 (continued) . . . . .	186
A.5	Experimental design for SC survey 2 . . . . .	187
A.5	Experimental design for SC survey 2 (continued) . . . . .	188
B.1	Experimental design for BWS case 1 survey . . . . .	197
B.2	Estimation results of the joint model . . . . .	208

## List of Figures

1.1	A typical shape for the diffusion process of an innovation (Rogers, 2010). . . . .	3
1.2	Taxonomy of varied behaviour (McAlister and Pessemier, 1982; Pessemier, 1985). . . . .	13
2.1	Illustration of choice scenarios in SC survey . . . . .	53
2.2	Example of the stated choice task in the questionnaire . . . . .	57
2.3	Responses to attitudinal statements . . . . .	58
2.4	Framework of the ICLV model . . . . .	61
3.1	Illustration of UberAIR service. . . . .	87
3.2	Example of SC tasks. . . . .	92
3.3	Parallel analysis scree plots for the factor analysis. . . . .	94
3.4	Structure of the 2L-LC model. . . . .	98
3.5	Modelling framework of the 2L-LV-LC model. . . . .	102
4.1	Framework of the joint model. . . . .	132
4.2	Illustration of choice scenarios in the SC survey. . . . .	140
4.3	Example of SC tasks. . . . .	141
4.4	Example of BWS1 tasks. . . . .	141
4.5	Example of BWS2 tasks. . . . .	143
A.1	Screening criteria in data collection. . . . .	178
B.1	Correlation between B-W scores and posterior sensitivities. . . . .	203
B.2	Framework of the HCM model. . . . .	204





# Abbreviations & Acronyms

A number of abbreviations and acronyms are used throughout this thesis. They are listed here for reference in alphabetical order.

<b>ASC</b>	Alternative-specific constant
<b>BIBD</b>	Balanced incomplete block design
<b>BWS</b>	Best-worst scaling
<b>BWS1</b>	Best-worst scaling case 1
<b>BWS2</b>	Best-worst scaling case 2
<b>B-W</b>	Best-minus-worst
<b>DCM</b>	Discrete choice modelling
<b>HSR</b>	High-speed rail
<b>IID</b>	Independently and identically distributed
<b>ICLV</b>	Integrated choice and latent variable
<b>ICT</b>	Information and communication technology
<b>IID</b>	Independently and identically distributed
<b>LC</b>	Latent class
<b>LL</b>	Log-likelihood
<b>MMNL</b>	Mixed multinomial logit
<b>MNL</b>	Multinomial logit
<b>RUM</b>	Random utility maximisation
<b>RP</b>	Revealed preference
<b>SC</b>	Stated choice
<b>SP</b>	Stated preference
<b>TNC</b>	Transport network company
<b>UAM</b>	Urban air mobility
<b>VOT</b>	Value of time
<b>VTOL</b>	Vertical take-off and landing
<b>WTP</b>	Willingness-to-pay



## Chapter 1

# General introduction

## 1.1 Context

Technological advancement has always been a dynamo that propels the development of society in different aspects and improves people’s living standards. In particular, technological development has contributed to the evolvement in transportation, in a manner that has tremendously shaped the way people explore the world and interact with each other. In the past decades, rapid technological development has catalysed many new passenger travel modes/services (e.g. high-speed rail, autonomous vehicles, electric vehicles, bike-sharing, ride-sourcing). It has also contributed to the increasingly prevailing new concept of *smart mobility* (Garau et al., 2016), which encompasses many different initiatives to improve people’s quality of life (Benevolo et al., 2016), including integrating those aforementioned transport innovations.

Smart mobility is a crucial component of the wider concept of *smart city* (Caragliu et al., 2011; Lombardi et al., 2012), which emerged as a result of increasing population and uncontrolled urbanisation (Garau et al., 2016).<sup>1</sup> This urbanisation process has brought about an imbalance between growing travel demand and limited transport resources. For example, while many big cities act as the hubs of transport networks, where many railway lines are intersected and a substantial number of flight transfers take place every day, reaching out to far-away destinations could be more difficult for people who live in small cities or rural areas, as they do not have as much good access towards various transport resources as people in big cities do. Within many large cities, people’s travel mobility is impaired due to the increasingly severe traffic congestion, resulting in a waste of travel time and an increase in pollution. Therefore, solely expanding

---

<sup>1</sup>There is not yet a unique definition for *smart city*. It is a complex and broad concept which respects sustainability, aiming to improve the quality of different aspects of life in urban space and characterised with the dependence on technologies, especially information and communication technologies (ICT).

transport capacities is not sufficient to ameliorate the contradiction between travel demand and supply due to resource shortages. Instead, it is imperative to improve the efficiency of the urban transportation system to achieve better travel mobility for a more sustainable society as a whole. In this sense, smartness is not only characterised by the use of advanced technologies (particularly information and communication technology, abbr. ICT), but also closely connected with a broad concept of sustainability. Herein, this thesis refers to smart mobility as *the ease, accessibility, connectivity, affordability, efficiency and environmental-friendliness of travelling around at different levels (e.g. transnational, national, regional)* (Benevolo et al., 2016; Docherty et al., 2018; Lyons, 2018; Zawieska and Pieriegud, 2018).

Technological development has sprouted new travel modes, forming different types of smart mobility. The introduction of these new modes results in changes of the characteristics of the transport system itself, which may consequently induce changes of various types of individual choice behaviour, e.g. choice of travel mode, choice of departure time, choice of routes, whether to purchase a private vehicles, which type of vehicles to purchase, etc. The evolution process of the overall uptake of an innovative mode in population level can be described based on the theory of diffusion, which describes the process of an innovation being “communicated through certain channels over time among the members of a social system” (Rogers, 2010). This diffusion process can be illustrated as an S-shaped curve (see Fig. 1.1) to show the cumulative number of adopters or the total percentage adoption over time. Specifically, when a new mode is introduced, some innovators would adopt the new mode at an early stage independently of the social influence. As the number of people who adopt the new mode grows, more and more knowledge about the new mode would become available and the risk of adoption reduces for the rest to decide whether and when to adopt the new mode. Consequently, an increasing number of people would imitate and adopt the new mode at the aggregate level. The growth rate of adoption at the outset is low, then rises gradually, and would eventually slow down (Bass, 1969; El Zarwi et al., 2017; Rogers, 1976, 2010).

This thesis investigates mode choice behaviour at the individual level in this new context where new smart mobility modes keep emerging and focuses only on the initial stage of the diffusion process. Some passengers may be shifted from existing modes to the new mode to make the same journey, while induced travel demand may also be generated as a result of the improved mobility brought about by the new mode. At the individual level, how an individual is exposed to the knowledge about the new mode and how (s)he perceives the attractiveness

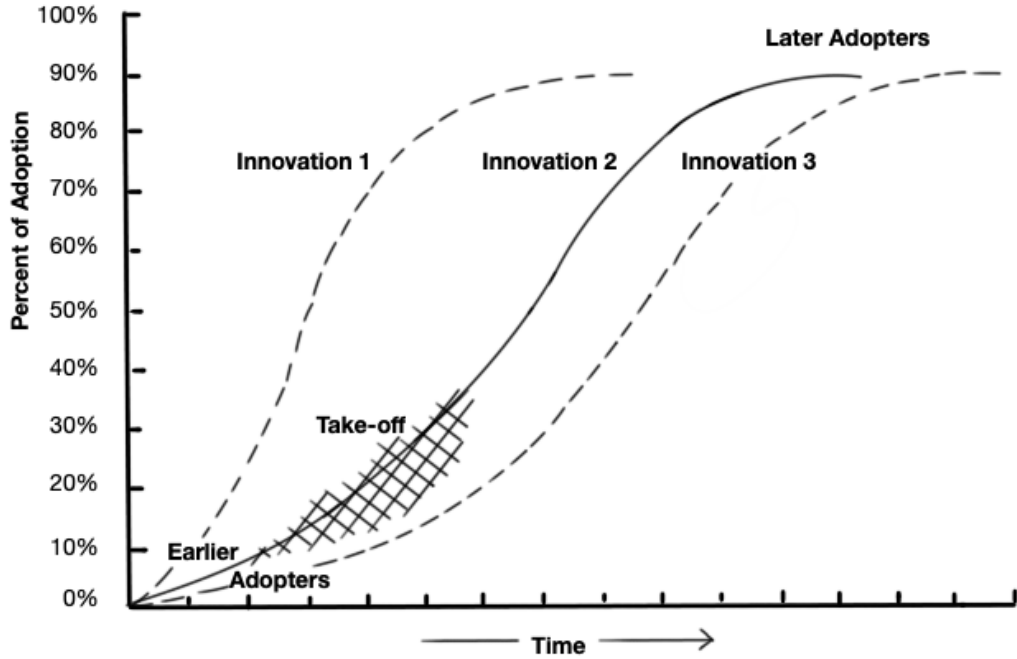


Fig. 1.1: A typical shape for the diffusion process of an innovation (Rogers, 2010).

of the new mode would affect the decision of adoption/rejection of the new mode (Rogers, 2010). Then a simple but foremost question for each individual when a new mode enters the market is *whether to adopt the new mode*. The answer is influenced by many factors, including some observable ones. For example, reduction in travel cost or travel time might attract more passengers who value cost or time; a smaller number of transfers brought about by the introduction of a new metro line might attract more passengers to travel by metro. Meanwhile, many unobservable factors (e.g. personalities, psychological factors, and habits) would also play a role in deciding whether to adopt or reject the new mode. For instance, while some people are more likely to risk trying the new mode at an early stage, others would wait to make decisions till they feel less risk; while some people are more strongly affected by the behaviour of other people, others make decisions more independently from the influence of social network. The impact of these factors may vary across respondents, and even across choice occasions over time for a given decision-maker (i.e. preference heterogeneity may exist). In particular, compared to the situation where all the available modes are familiar to the decision-makers, mode choice behaviour may additionally present unique characteristics when a new mode enters the market, which can be manifested in the following three aspects, requiring more research attention. This thesis would focus on these three aspects.

- Firstly, while some people intrinsically prefer exploring novel travel expe-

riences, others would be more inclined to avoid changes and stick to their habitual travel experiences.

- Secondly, it may also be likely that some people have stronger tendencies to vary their choices over time frequently, whereas others' choices remain relatively more stable.
- Finally, as a new mode may exhibit some new attributes specific to itself, the unfamiliarity to new attributes could bring about uncertainties to individuals in terms of the ways they evaluate the importance of various attributes when making choices.

The changes of individual mode choices eventually affect modal split and travel demand at a market level. It is crucial to understand how a new mode affects the market-level travel demand.<sup>2</sup> This is because travel demand models reflect whether people can be nudged towards more sustainable and environmentally-friendly modes. Since a new mode usually exhibits some specific features, existing mode choice models cannot be directly used to analyse individual choice behaviour in the new context. Even if the new mode is not characterised with any new attributes, it is difficult to prove existing discrete choice estimates using SC data without the new mode are sufficient to explain choice behaviour in the new context. Instead, it is necessary to conduct fit-for-purpose analyses to uncover travel demand through disaggregate approaches based on individual-level data. Compared to aggregate approaches, disaggregate methods can account for preference heterogeneity across individuals, and treat the price variable as exogenous, enabling the examination of value-of-time and willingness-to-pay estimates in the context of the introduction of a new mode.

This thesis looks at two representative facets of smart mobility, namely *intermodal mobility* and *shared mobility*. They are expected to contribute to ameliorating the accessibility and congestion issues raised above. Specifically, high-speed rail(HSR)-air intermodality is examined for the first facet. This novel mobility service enables passengers to jointly use HSR trains and air for a same journey without the hassle of separately purchasing tickets with the ticketing integration system. It is expected to increase the connectivity of a transport network<sup>3</sup> by treating HSR as a feeder leg of air travel, such that passengers living

---

<sup>2</sup>Market-level travel demand can be elicited through either aggregate approaches or disaggregate approaches. While the former uses market-level data to explain market-level demand, the latter uses individual-level data to get individual-level demand and then aggregates over individuals to obtain market-level demand (Train, 2009).

<sup>3</sup>Connectivity can be defined as “the degree to which nodes in a network are connected to each other” (Burghouwt and Redondi, 2013).

in a wider catchment area of the airports could have better accessibility<sup>4</sup> to long-distance or trans-national flights at big cities. This intermodal mobility practice may also help congested airports to divert short-and-medium-haul flight demand to HSR to mitigate congestion. Regarding the second facet, this thesis looks into the upcoming air taxi service together with other existing ground-based shared mobility services. The new air taxi service is anticipated to increase the ease of moving around within congested metropolises by extending shared mobility services into the third dimension and forging urban air mobility (UAM).

Given this, the major task of this thesis is to examine mode choice behaviour at an individual level and uncover travel demand in the new context of HSR-air intermodality and air taxi, respectively. Importantly, the three unique behavioural features aforementioned (i.e. novelty-seeking, alternation, and attribute importance) are studied in this thesis to detect their role in affecting mode choices after the introduction of the new modes.

Methodologically, discrete choice modelling (DCM) forms the backbone of this thesis. This is mainly due to the fact that DCM, being a well-established econometric method, makes it possible to both explain the heterogeneous individual choice behaviour and obtain the aggregate travel demand at a market level.

This introduction chapter reviews related work before identifying research gaps. The data used in this thesis is subsequently summarised. The research objectives together with the implementation plans are then presented in detail. Finally, the work of and contributions made by each chapter (with the exception of the conclusion chapter) are summarised.

## 1.2 Related work

Prior to identifying research gaps and objectives, it is necessary to review the methodological background as well as existing theoretical and empirical studies. This section first summarises studies on HSR-air intermodality and shared mobility services, including but not limited to mode choice behaviour in the new context. Then, psychological and behavioural evidence is presented to manifest the unique features individuals exhibit when confronted with something new and unfamiliar. This review next briefs different types of data usually used for preference elicitation in DCM-based travel behaviour studies. Finally, it provides

---

<sup>4</sup>A popular definition of accessibility is given by Hansen (1959) as “*a measure of the intensity of the possibility of interaction*”, which is inversely proportional to some functions of the distance between an individual and the area of opportunities.

an overview of the DCM-based representation of preference heterogeneity that serves the subsequent chapters.

## 1.2.1 Transport background

This section provides background information of the two new smart mobility services of interest, i.e. HSR-air intermodality and shared mobility, with respect to the terminology and analysis methods.

### 1.2.1.1 Intermodal mobility: HSR-air intermodality

#### Terminology

*Intermodality* is originally related to freight transport and later on extended to passenger transport, with an aim to achieve optimal integration of different transport modes. It is defined by [Commission of the European Communities \(1993\)](#) that “*Intermodality is a characteristic of a transport system that allows at least two different modes to be used in an integrated manner in a door-to-door transport chain.*”

The European Union has long been devoted in promoting the sustainable intermodal passenger transport across Europe and according to one of the many EU-founded projects that examined this issue, the concept of intermodal passenger transport is given as “*Passenger intermodality is a policy and planning principles that aims to provide a passenger using different modes of transport in a combined trip chain with a seamless journey.*” ([European Commission’s Directorate-General for Mobility and Transport, 2010](#)). Intermodal passenger transport could take place on different levels ([Gebhardt et al., 2016](#); [Willing et al., 2017](#)), e.g. short-distance intracity level (e.g. park-and-ride) and long-distance intercity level (e.g. HSR-air intermodality).

The research related to the complementarity between air and rail started by [Stubbs and Jegede \(1998\)](#) with a purpose of understanding the possibility of railway trains serving as an access to the airport for passengers, emphasizing that only a rail-air link that can integrate the airport rail station with the main railway network closely can attract enough passengers for intermodal travel. [Givoni and Banister \(2006\)](#) conducted an initial examination of the scope and limitations of such integration at Heathrow airport, and [Givoni and Banister \(2007\)](#) explored the rail’s role in air system that includes both being an access mode and acting as feeder flight.

With the rapid development of HSR network, researchers and policymakers have started promoting cooperation on top of competition between HSR and



air, with respect to infrastructure (e.g. rail track into airport terminal), train operation (e.g. schedule coordination), and information services (e.g. integrated ticketing system, code-sharing agreement). In the context of HSR-air intermodality, HSR services are treated as feeders to airlines on additional spokes from a hub airport to complement and (or) substitute existing air services (Givoni and Banister, 2006). In Chapter 2 and Chapter 4, which are set in the context of HSR-air intermodality, the terms of “intermodal”, “integrated”, “connected” and “cooperative” are used interchangeably.

### Analysis methods

A latest critical review by Zhang et al. (2019) concluded that the impact of HSR-air intermodality on airport traffic depend on “*the airport’s accessibility to HSR inaccessibility markets, its attractiveness to passengers from competing airport, as well as changes in market structure of the city-pair markets.*” Regarding congested hub airports without enough space for building further runways, airports together with airline companies are actually in need of seeking substitutional transport resources to serve the growing medium-and-long haul travel demand. HSR-air intermodality is helpful to shift feeder-leg and short-haul air passengers to HSR and mitigate airport congestions (Vespermann and Wald, 2011). Apart from this effect, Zhang et al. (2019) also pointed out other potential impacts by the entry of HSR-air intermodality on travel demand. For example, it is possible that the feeder role of HSR brings about more connecting passengers and increases airport congestion. In contrast, cooperation between HSR and air at small and non-congested airports accompanied by enhanced international connections can attract passengers from primary congested hub airports. Additionally, it is suggested that new demand for HSR-air intermodal travel may be induced, especially for areas which used to be underserved by air transport but now within the catchment of the airport due to the connection made by HSR.

Mode choice studies on long-distance passenger travel usually only involve single direct modes as choice alternatives, while much fewer analysts regard connecting modes as available alternatives as well (Allard and Moura, 2016). This hinders the understanding and marketing promotion of intermodal travel behaviour at an intercity level. Nevertheless, recent research has already begun looking at such “connecting mode” as a choice alternative which can compete with other connecting modes or direct modes.

Among the limit empirical studies on mode choices (see Table 1.1) among HSR-air and other available alternatives, SP surveys have been used to collect information on individual preferences (e.g. Brida et al., 2017; Chiambaretto

et al., 2013; Li and Sheng, 2016; Martín and Román, 2013; Román and Martín, 2014). Apart from travel time and travel cost which are included in most mode choice studies, many other different attributes of a (connecting) mode have been taken into consideration to account for their influence on individuals' mode choice behaviour in the context of HSR-air intermodality. For example, connectivity is regarded as a decisive factor and a seamless transfer between air and HSR can best attract passengers from other modes to HSR on the feeder leg (Givoni and Banister, 2006). Whether there is compensation in case of delay also becomes more important compared to the case of choosing among single modes. Integrated luggage handling system has already been deployed in Frankfurt airport as such measure can facilitate passengers with heavy or many pieces of luggage, especially for long-haul travel. Another study highlights the vital role of transparent transport information as well as integrated ticketing (Sauter-Servaes and Nash, 2009). This is because mono-modal online ticketing systems make it difficult for passengers to compare the utility of different modes for a given journey; besides the inconvenience of purchasing separate tickets on different websites is a barrier that prevents passengers from making a multi-legs journey.

**Table 1.1:** Attributes considered in mode choice analyses in the context of air-HSR intermodality

<b>Literature</b>	Chiambaretto et al. (2013)	Brida et al. (2017); Martín and Román (2013); Román and Martín (2014)	Zanin et al. (2012)	Li and Sheng (2016)
Access time		✓		✓
Travel time		✓ (in-air+in-train)	✓ (in-train)	✓ (in-air+in-train)
Connecting time	✓	✓		✓
Protection against delay	✓			
<b>Attributes</b> Travel cost	✓	✓	✓	✓
Ticket integration		✓		
Waiting time			✓	✓
Luggage integration	✓	✓		
Service in the train	✓			
<b>Alternatives</b>	different air-rail options	air-HSR, air-air	focuses on feeder-leg: car, conventional rail, HSR, air	air, HSR, air-HSR

### 1.2.1.2 Shared mobility

#### Terminology

Since ambiguity exists in terms of the definitional boundaries of shared mobility and how the term “shared” should be interpreted, etc., it is difficult to have a precise common definition for shared mobility (Le Vine and Polak, 2015). Nevertheless, a consensus has been reached on a significant characteristic that users of shared mobility could have short-term access to travel services on an as-needed basis, rather than purchase, own, and operate vehicles solely for personal needs (Le Vine and Polak, 2015; Shaheen et al., 2016).

Shared mobility services can generally be differentiated according to what is shared. Different types of transportation modes could be shared, resulting in services such as carsharing and bikesharing. Shared mobility also includes shared ride services, for example, conventional ridesharing (e.g. carpooling, van-pooling), on-demand ride services (e.g. ridesourcing or ridehailing or transport network companies, ridesplitting, E-hailing), and alternative transit services (e.g. paratransit, microtransit). Herein, it is worth distinguishing between traditional ridesharing and newly popularised on-demand ride. The former enables drivers and passengers with similar origin-destination pairings to share rides. The latter is characterised with the usage of ICT which implements real-time matching between demand and supply, such that pre-arranged or demand-responsive travel services can be provided upon request as long as mobile devices (e.g. smartphones, tablets) are connected to the internet. Specifically, ridesourcing (e.g. UberX, UberSELECT) is the major component of on-demand ride services that matches drivers of private vehicles with passengers; ridesplitting (e.g. UberPOOL) is a pooled version of ridesourcing which allows sharing a ride at a reduced cost with other poolers travelling on a similar route; E-hailing is a similar service to ridesourcing which is provided by taxi drivers rather than private vehicle owners. (Cohen and Shaheen, 2018; Jin et al., 2018; Shaheen and Chan, 2016; Shaheen and Cohen, 2019; Shaheen et al., 2016).

An emerging direction of on-demand shared ride services involves the deployment of automation technology, such that users can gain access to shared automated vehicles, which has the potential to reduce traffic congestion and fuel emission as well as the risk of inducing much additional travel demand (Fagnant and Kockelman, 2015). As vehicles would be driverless, the differences between ridesharing and ridesourcing (including its variations like ridesplitting and E-hailing) would become more negligible in this context.

Furthermore, the relatively new concept of urban air mobility (UAM), which could be regarded as an extension of shared mobility in the air, has been put

forward and gained increasing research and investment attention. UAM would be operated within on-demand ride service networks and supported by automation technologies as well as distributed electric propulsion technologies, such that travellers would in the future be served by air taxis upon requests through internet-based mobile devices (Goyal, 2018).

### **Analysis methods**

Various methods have been adopted to evaluate the impacts of on-demand ride services on urban development, to assess or optimise the system performance of on-demand ride service networks, and to improve the understanding of individual behaviour in the new context accordingly, etc. The research predominantly focuses on ground-based services, whereas little effort has been devoted to UAM. What discussed in the next revolves around ground-based on-demand ride services, including but not limited to mode choice analysis, which could to some extent provide methodological insights to UAM analysis.

Shaheen et al. (2016) and Cohen and Shaheen (2018) pointed out based on existing practices and research that ridesourcing could improve the accessibility and mobility to travel services with lower cost and commute stress, especially for non-vehicle owners where and when the travel needs could not effectively be covered by public transport. Moreover, ridesourcing would not only induce travellers' behaviour changes but also influence the labour market as it allows vehicle owners to make a profit using their own vehicles. A recent literature review by Jin et al. (2018) summarised that although ridesourcing complements public transport as it could help solve the first/last mile issue, it generates an unclear influence on mitigating traffic congestion and greenhouse emissions. Moreover, it is suggested that ridesourcing may worsen the inequality of accessing emerging technologies as the new shared service may benefit only a subset of population, whilst data security is another challenging issue confronted by the ridesourcing industry.

Mathematical models have been widely established to address the interaction between demand and supply in the context of different types of on-demand shared ride services. Key issues like ridematching between travellers and drivers (e.g. Rasulkhani and Chow, 2019; Zha et al., 2018, 2016) and fare pricing schemes (e.g. Djavadian and Chow, 2017; He et al., 2018; Zha et al., 2017), etc. have been examined through establishing equilibrium models. These results could provide operational strategies to service providers and policy support to policymakers under different market and behavioural scenarios. Apart from building mathematical models, agent-based simulation techniques are been increasingly applied

to mimic individual behaviour in the real world which could be heterogeneous and dynamic, or to validate the assumption or argument made in mathematical models (e.g. [Djavadian and Chow, 2017](#); [Fagnant and Kockelman, 2018](#)).

Another body of literature relies on individual-level real-world data to explain choice behaviour and predict travel demand. This can be achieved by estimating discrete choice models or other statistical models. For example, [Dias et al. \(2017\)](#) estimated a binary ordered probit model to understand the driving factors behind the adoption of carsharing and ridesourcing. [Chen et al. 2018](#) analysed revealed transaction data and stated preference data, and concluded that ridesplitting is conducive to the alleviation of traffic congestion, the increase of vehicle seat occupancy, and the reduction of vehicle emissions. [Krueger et al. \(2016\)](#) adopted a mixed multinomial logit discrete choice model using stated preference data to uncover the impact of various socio-demographic characteristics, level-of-service attributes on travellers' adoption of the new shared autonomous vehicles. In addition, machine learning has been increasingly adopted to unveil choice patterns and forecast travel demand given the availability of large-scale individual-level behavioural data (e.g. [Chen et al., 2017](#); [Ke et al., 2017](#)).

## 1.2.2 Behavioural underpinning

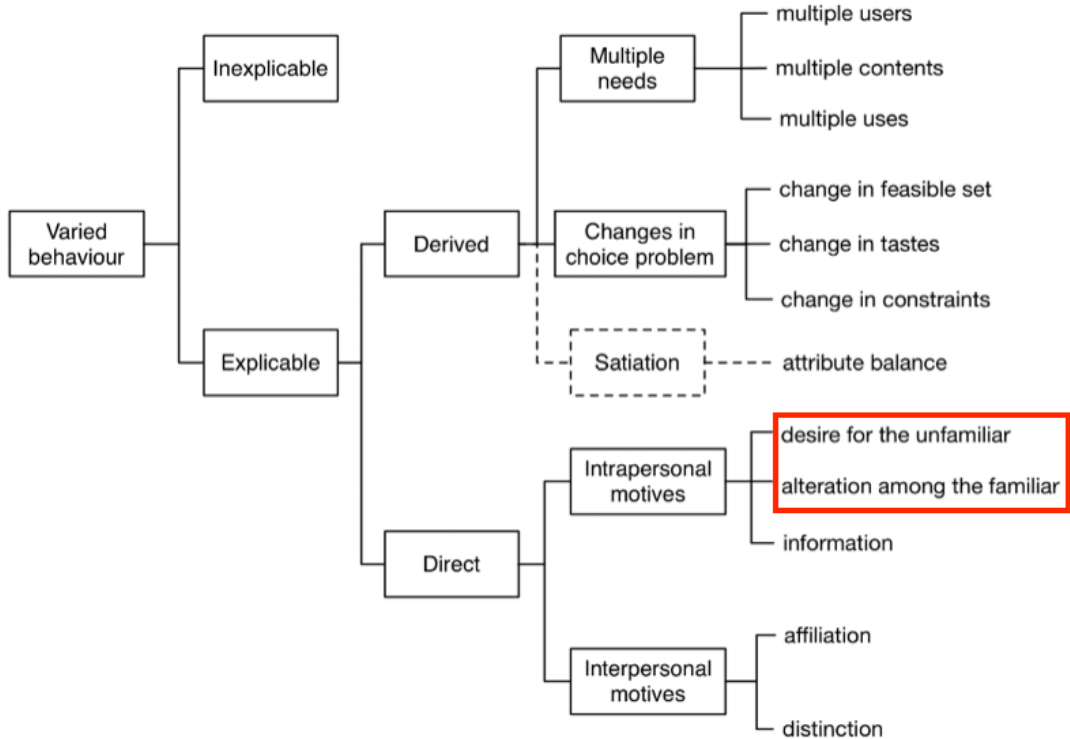
As stated in section 1.1, the entry of new smart mobility services could result in changes in mode choice behaviour, even induce new travel demand. Given this, it is necessary to move beyond merely understanding the impact of various alternative-specific and level-of-service attributes on decision-making when examining individual mode choice behaviour in the new context. That is, it is important to further investigate the unique behavioural features appeared when new travel modes are involved. This section, therefore, reviews relevant studies, revolving around the three unique characteristics mentioned in section 1.1, so as to provide behavioural underpinnings for the subsequent three chapters.

### 1.2.2.1 Variety-seeking

#### **Terminology: two aspects of variety-seeking**

[McAlister and Pessemier \(1982\)](#) and [Pessemier \(1985\)](#) classified varied behaviour into different types according to the cause behind it. As shown in Fig. 1.2, varied behaviour (i.e. switching) can either be regarded as inexplicable or explicable to researchers, though these two types of models have gradually converged. Different reasons could cause changes in one's behaviour. They suggested that individuals' varied behaviour could not only be extrinsically derived as a result

of other triggers (e.g. changes in the choice problem) but also be attributed to intrinsic direct motives. The direct motives include intrapersonal motives (e.g. desire for exploring something unfamiliar, alternation among the familiar) and interpersonal motives (e.g. desire for social distinctive, need for affiliation with the public). The variety-seeking phenomenon can be attributed to the direct motives shown in Fig. 1.2 as it is more intrinsically motivated rather than extrinsically derived (Trijp et al., 1996).



**Fig. 1.2:** Taxonomy of varied behaviour (McAlister and Pessemier, 1982; Pessemier, 1985).

Ha and Jang (2013) suggested that the two aforementioned types of intrapersonal motives, i.e. the desire of either choosing a new alternative (*novelty-seeking*) and changing selections among familiar alternatives (*alternation*), could be defined as variety-seeking behaviour. Thus, the concept of *variety-seeking* discussed in this thesis falls in the red box in Fig. 1.2. These two aspects of variety-seeking relate to the first two unique features listed in section 1.1, respectively.

*Novelty-seeking* describes the tendency to explore something new and unfamiliar. One prevailing definition of novelty-seeking in literature is “the degree of contrast between present perception and past perception” (Lee and Crompton, 1992).

*Alternation* can be defined as the phenomenon of an individual choosing a different alternative from his or her choice set over time due to the utility derived

from the change itself, irrespective of the alternative that the decision-maker switches to or from (Borgers et al., 1989; Givon, 1984).

### Analysis methods

Some variety-seeking studies explicitly specify the mathematical structure of switching, with an emphasis on the alternation aspect of variety-seeking. For example, Givon (1984) proposed a model with an assumption that “the responsibility of choosing alternative  $j$  given alternative  $i$  was chosen on a previous occasion is a function of the preference for alternative  $j$  and the preference for switching”. Borgers et al. (1989) focused on transition probability in recreational choices, assuming that the deterministic component of an alternative’s utility not only depends on alternative-specific attributes but also on the (dis)similarity between the current chosen alternative and the previous chosen alternative, such that the probability of choosing differently in two consecutive occasions was a function of this (dis)similarity. Chintagunta (1998) developed a new brand switching model based on hazard function which allowed the brand choice probabilities to vary over time and found that variety seekers are more likely to purchase a brand positioned farthest away from the previous purchased brand.

In another stream of studies, psychometric scales have been created as tools to measure variety-seeking tendencies and most of them are context-specific (e.g. Baumgartner and Steenkamp, 1996; Lee and Crompton, 1992; Pearson, 1970; Pessemier and Handelsman, 1984; Trijp et al., 1996; Wills et al., 1994). The statements in the scales of variety-seeking usually do not clearly distinguish between the novelty-seeking aspect and alternation aspect as these two aspects are essentially correlated and interwind. Responses gained from psychometric scales can be used independently to segment market (e.g. Assaker and Hallak, 2013; Van Trijp and Steenkamp, 1992). Those responses can also be used through Structural Equation Modelling to analyse the correlation between variety-seeking tendencies and other behaviours, e.g. Jang and Feng (2007) examined the relationship between novelty-seeking and tourists’ intentions to revisit destinations. Those responses could also be jointly estimated together with choices in discrete choice models, e.g. Rieser-Schüssler and Axhausen (2012) treated variety-seeking as a latent variable in the choice model, while the latent variable was also used to explain the responses to the statements in the scale of variety-seeking.

### Role in choices

This thesis follows the second stream of studies. It regards variety-seeking as a psychological construct (personal trait) that describes the attitudes/tendencies



towards switching behaviour rather than trying to describe the state of switching. In our study, variety-seeking tendencies are assumed to be individual-specific and remain constant within an individual across choices. Accounting for the role of this unobserved psychological construct can enable researchers to achieve a more meaningful interpretation of choices and segment the consumer market with efficient marketing strategies.

### 1.2.2.2 Attribute importance under uncertainty

Confronting a new product may lead to uncertainty in respondents' decision-making. [Kalish \(1985\)](#) pointed out that uncertainty appears due to a lack of experience information about the new product, especially towards those attributes of which information can only be revealed through using. It is argued that the uncertainty associated with the new product reduces as the experience information is accumulated, for example when the number of adopters of the new product increases in the market.

Similarly, as in the real-world market, uncertainty could also emerge in a hypothetical choice environment where respondents are required to make choices among a set of alternatives including a new alternative exhibiting new and unfamiliar attributes.

This uncertainty could influence individuals' attribute processing when making choices. Regarding those new attributes, some respondents might feel uncertain whether the new attributes are important to them and how much weight should be placed on these new attributes in relative to other more familiar attributes ([Kahn and Meyer, 1991](#)).

Under the uncertainty caused by new alternatives and new attributes, individuals may adopt simplification strategies when making choices, such as only considering a subset of attributes ([Hensher, 2010](#)), sticking to status-quo option and making more random choices ([Dekker et al., 2016](#)). Thus, some individuals could lower the risk by underestimating the importance of new attributes, while others may excessively perceive the importance of these new attributes.

As such, multiple types of preference elicitation methods have been jointly used to better understand how people evaluate the importance of different attributes under uncertainty in the context of new alternatives. For instance, aside from the conventional stated choice (SC) tasks, some studies directly ask respondents how certain they are of their choices in each choice task through a Likert scale (e.g. [Dekker et al., 2016](#)), or whether a specific attribute is considered during decision-making (e.g. [Hensher, 2006](#); [Hensher and Rose, 2009](#)). The stated 0-1 attribute (non-)attendance could also be used in a continuous way to ac-

commodate the impact of attribute importance. For example, [Hess and Hensher \(2013\)](#) assumed that for each attribute, respondents perceive a value of the underlying attribute importance, which is not observable but can be treated as a latent variable in a discrete choice model to explain the heterogeneity in marginal sensitivities as well as the responses towards the attribute (non-)attendance questions in the measurement equations.

### 1.2.3 Preference elicitation methods

Stated preference (SP) data and revealed preference (RP) data have been intensively and widely used in the field of discrete choice modelling, and in the transport realm in particular. RP data is collected from actual choice observations in a real-world environment so that RP data is not applicable in situations where an alternative of interest has not yet entered the market. In contrast, SP surveys can be used to retrieve people's preferences in hypothetical situations ([Ben-Akiva et al., 2019](#); [Train, 2009](#)).

A SP survey can come in different formats, e.g. stated choice survey, best-worst scaling survey, rating survey, ranking survey, etc. This section briefly describes the basic principles of the preference elicitation methods used in this thesis. This section can be jointly read with section 1.4 which summarises the empirical information of the surveys and data used in the subsequent three chapters of this thesis.

#### 1.2.3.1 Rating data

Rating method directly asks respondents to state their preferences. A rating task normally requires an individual to give a point for each item based on a given Likert scale (e.g. a psychometric scale), with each point corresponding to a specific level of the preference.

Despite the easiness in conducting a rating survey, rating method has its own limitations. Firstly, rating method could easily lead to bias, as respondents may respond to the scale in different ways, such that some people prefer to avoid extreme options while others are opposite; or some people tend to use more scale points whereas others prefer fewer ([Software, 2013](#)). Secondly, respondents do not need to make serious trade-offs between items and thus some of them may rate everything being the same important. Therefore, data gained from rating tasks cannot provide adequate valuable information about discrimination of preferences, making it difficult for researchers to interpret the real priorities of each item ([Finn and Louviere, 1992](#)).

### 1.2.3.2 Stated choice data

Stated choice (SC) data plays an important role in applying discrete choice modelling techniques for preference elicitation and choice behaviour analyses.<sup>5</sup> A SC survey could consist of a one-off choice task, forming cross-sectional data, or include multiple choice tasks, forming panel data, i.e. more than one choice observation is recorded from each respondent. A typical SC survey with a panel of repeated choice tasks is usually obtained from a specific choice experiment design, e.g. orthogonal design, fractional factorial design,  $D$ -efficient design. Each SC task consists of a finite set of alternatives, where each alternative is depicted by a combination of attributes, each attribute taking a certain level value.

The choice experiment usually imitates the real-world choice situations to a certain degree and requires respondents to state their preferences amongst different alternatives in hypothetical choice situations. Therefore, SC data could be used to understand preferences towards new alternatives which are not observed in real-world situations. This also allows greater variations in attribute levels of SC data, whereas RP data collected from a real-world market usually have limited variations in attribute values. SC data can thus enable researchers to better analyse trade-offs among different attributes, especially in situations where an existing alternative exhibits new attributes which are not yet observed in the real-world market or where attribute levels take values much different from what have been observed in the real-world market (Hensher, 1994).

### 1.2.3.3 Best-worst scaling data

A best-worst scaling (BWS) survey (Finn and Louviere, 1992) usually presents respondents with a series of choice sets and requires them to make discriminating choices for both the *best* and the *worst* items from each choice set which consists of at least three items. The notions of “best” and “worst” could stand for different concepts as required by the research objectives, with a common idea that they represent the two extremes of a “*continuum*”.<sup>6</sup> Since a BWS task requires respondents to consider two extremes on the underlying scale from a relatively small choice set, it is considered easier to respond than in rating or ranking tasks. As such, BWS approach outweighs rating or ranking method as it can take advantage of respondents’ tendency of responding more consistently and accurately to extreme options (Marley and Louviere, 2005). Though BWS tasks may be more tedious than rating and ranking methods from the perspective of survey participants, BWS data can provide much more “*readily understandable*” and

---

<sup>5</sup>See Louviere et al. (2000) for detailed introductions to SC methods.

<sup>6</sup>See Louviere et al. (2015) for detailed instructions to BWS methods.

“*managerially meaningful*” results to analysts (Finn and Louviere, 1992).

There are three types of BWS surveys which differ mainly in respect of the complexity of items in the choice set. BWS case 1 (BWS1) measures a list of objects (e.g. attributes) themselves on an underlying scale, without the consideration of their values (e.g. attribute levels). The results can assist policymakers to understand the relative importance of attributes per se and where the improvement of service should be carried out in a relatively straightforward way (Auger et al., 2007; Louviere et al., 2013; Marti, 2012). The balanced incomplete block design (BIBD, Hanani 1975) is the most frequently used experimental design method to organise various to-be-assessed items into a number of choice sets. With BIBD, each item occurs the same often and co-occurs with any other item the same often across all the choice sets which are of the same size.

BWS case 2 (BWS2) compares among different attribute levels within a profile of an alternative at a common underlying utility scale (Flynn et al., 2007, 2008). A profile means a combination of attribute levels that describes an alternative, and each attribute can take the values of two or more attribute levels. Those attribute levels within a profile constitute a choice set, from which respondents need to pick the best and worst attribute levels. Through a BWS2 survey, both the relative importance of attributes and the relative gaps between different attribute levels in terms of “utility” can be inferred.

BWS case 3 (BWS3), compares among different alternatives, each depicted by a profile comprised of various attribute levels. Respondents need to pick the best and worst alternatives (i.e. profiles) from each choice set. A BWS3 survey is similar to a conventional SC survey except for that both best and worst alternatives need to be selected (Adamsen et al., 2013; Marley and Pihlens, 2012). BWS3 is more complex than BWS1 or BWS2, as the latter are both direct preference elicitation approaches, which present respondents with choice tasks out of multi-alternative settings and do not require trade-offs among alternatives.

#### 1.2.4 Representation of preference heterogeneity

Decision-making is influenced by many factors. Different people may be affected by different factors. The extent to which people are influenced by a same factor may also differ across individuals, sometimes even across choice occasions. Hence, it is crucial to accommodate preference heterogeneity when analysing choice behaviour and uncovering travel demand.

Discrete choice modelling (DCM) provides useful tools for researchers to analyse and forecast individuals’ choice behaviour, and in particular to address preference heterogeneity in decision-making. The majority of DCM applications are

conducted under the decision paradigm of Random Utility Maximisation (RUM) theory (McFadden, 2001; McFadden et al., 1973).<sup>7</sup> It is presumed that a decision-maker can derive some utility from choosing a particular alternative. The alternative is profiled by a set of observable attributes, each contributing partly to the utility of that alternative and influencing choice behaviour. Some other observable factors (e.g. socio-demographic characteristics of the decision-maker) may also explain part of the utility of that alternative. Under RUM theory, the utility of an alternative is not deterministic from the analyst's perspective, as apart from the systematic (deterministic) utility, there remains a random error in the utility which cannot be explained by the analyst but influences the decision-maker's choice behaviour.<sup>8</sup> The process of choice is considered compensatory, i.e. bad performance of one attribute of an alternative could be compensated by the good performance of another attribute of that alternative. Consequently, from the analyst's perspective, the alternative with the highest systematic utility has the highest probability to be chosen by the decision-maker.

This section puts an emphasis on reviewing the different representation of preference heterogeneity within RUM-based choice models. The following paper chapters would take these different types of preference heterogeneity into account when establishing discrete choice models.

---

<sup>7</sup> Alternative decision paradigms in DCM have been proposed to achieve more behaviourally realistic representation. For example, Chorus et al. (2008) and Chorus (2010) proposed Random Regret Minimisation (RRM) models based on Regret Theory, assuming that a decision-maker chooses the alternative that minimises anticipated regret. Other representative paradigms include the Elimination by Aspects paradigm proposed by Tversky (1972) and Decision Field Theory initiated by Busemeyer and Townsend (1993). The analyses in this thesis focus on the relative valuation of various attributes in affecting individual choice behaviour, rather than providing precise forecasts of travel demand or exploring the decision process adopted by decision-makers in reality. Thus, the choice models presented in this thesis are all developed on the RUM paradigm due to its widespread and dominant use in analysing choice behaviour in travel.

<sup>8</sup>In most RUM-based discrete choice models, the systematic utility is usually specified as a linear and additive function of explanatory variables and parameters. Different specifications of the random error in the utility functions result in different types of discrete choice models with different specifications of choice probabilities. For example, Multinomial Logit Model assumes independently and identically distributed (IID) type I Extreme Value distribution; Multinomial Probit Model assumes IID Normal distribution; Nested Logit model assumes the unobserved part of utility for all alternatives are jointly distributed as a generalised extreme value (GEV) (see Train (2009) for detailed introductions to DCM).

### 1.2.4.1 Systematic vs. random preference heterogeneity

Systematic preference heterogeneity is related to the observed variables and can be handled by allowing for the interaction between some socio-demographic characteristics and the alternative attributes or through using the socio-demographic variables as alternative-specific variables (Vij et al., 2013). For example, in a mode choice study in the Toronto-Montreal corridor, a MNL model is established, with income, gender, travel group size and a large city indicator being considered for accommodating systematic preference heterogeneity (Bhat, 1998).

Additionally, there might remain some unobserved psychological factors (e.g. attitudes, perceptions) which affect individuals' preferences and consequently influence choice behaviour. Accounting for their impacts could improve the behavioural explanatory power of the choice model. Given that these psychological factors are difficult to detect and measure from the analyst's perspective, directly incorporating them as explanatory variables in the utility functions of a discrete choice model could result in measurement error and endogeneity bias. Instead, Integrated Choice and Latent Variable (ICLV) model (Ben-Akiva et al., 2002a,b) could be adopted, where these factors are accommodated as latent variables to explain the choices, and in the meantime, to explain responses towards attitudinal statements developed for the underlying psychometric construct. In an ICLV model, latent variables are usually determined by observable variables (e.g. socio-demographic characteristics) in the structural equations, which are usually specified in a linear-in-parameter format together with a normally distributed disturbance. Therefore, the latent variables can explain part of the systematic preference heterogeneity across individuals.

However, even when all socio-economic characteristics are the same for different people, they may still have various preferences just because they are different people and their tastes vary purely randomly. This random preference heterogeneity can be incorporated in a mixed multinomial logit (MMNL) model, which assumes that coefficients for certain attributes are random and vary across respondents or includes an additive stochastic error term in the utility function such that the alternative-specific constant (ASC) for a given alternative essentially varies across respondents. Alternatively, the randomness in preference heterogeneity can be handled in a latent class (LC) model by assuming that there are a finite number of classes of respondents and each class is characterised with distinct preference patterns. By doing so, preferences vary across different classes of respondents and preference heterogeneity can be captured by probabilistically assigning membership to each respondent (Walker and Ben-Akiva, 2002). Comparisons between the latent class model and mixed logit model can

be found in some literature ([Greene and Hensher, 2003](#); [Shen, 2009](#)). Moreover, latent and mixed logit can be combined to allow for continuous randomness in preference heterogeneity within a class by specifying a random parameter latent class mode ([Greene and Hensher, 2013](#)).

#### 1.2.4.2 Inter-individual vs. intra-individual preference heterogeneity

Accommodating systematic and random preference heterogeneity across individuals could lead to a more behaviourally realistic recovery of preferences and demand forecast. Apart from this inter-individual preference heterogeneity, intra-individual preference heterogeneity may also exist such that an individual's preferences may not remain unchanged across different choice occasions.

In situations where each individual is only required to respond to a single stated/revealed choice, it is unnecessary and impossible to consider intra-individual preference heterogeneity as each choice response is obtained from a different respondent. However, if a RP survey requires an individual to reveal multiple history choices, the preferences of that individual may evolve over time in the real-world market as external factors may influence the individual's preferences. Regarding a SC survey which presents an individual with multiple hypothetical choice tasks, it is usually deemed that preferences remain stable over choice tasks as SC data is collected in a single setting, rather than over a relatively longer time span as RP data does. Nevertheless, the preferences of a given individual still may change over stated choice tasks because of learning effect, cognitive burden, etc, such that preferences may vary across choice tasks within a given individual when completing the SC survey ([Hess and Rose, 2009](#)). Ignoring the existence of intra-individual variations could mislead preference elicitation and demand forecast ([Ben-Akiva et al., 2019](#)).

For most of the preference recovery studies using panel SC data, it is assumed that the preferences of an individual remain stable across choices. Nevertheless, growing attention has been placed on accommodating inter-and-intra preference heterogeneity, and the advancement in computing power enables a more complex representation of individuals' preferences and decision-making. A common practice to account for preference variations both across respondents and across observations is to establish a model within the MMNL 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 observations are specified (e.g. [Hess and Giergiczny, 2015](#); [Hess and Rose, 2009](#); [Hess and Train, 2011](#)). However, this is achieved at a high computational cost because the calculation of the

resulting log-likelihood involves integration over random distributions at both layers (Hess and Train, 2011). Recently, Becker et al. (2018) introduced a Hierarchical Bayes estimator for MMNL models with both inter-and-intra individual preference heterogeneity, leading to a substantial reduction in computational time. Given that both MMNL and LC models can accommodate preference heterogeneity with the latter being much easier to estimate, Hess (2014) raised the question “whether replacing one layer with weighted summation through a latent class structure would be beneficial”. It is suggested the preference heterogeneity across respondents can be replaced by a latent class structure, leaving only one layer of integration over observations in estimation.

### 1.3 Research gaps

The previous section provides an overview of studies related to mode choice behaviour when new smart mobility services are introduced, from which research gaps could be identified. This section summarises the gaps in existing literature from the perspective of behaviour which are addressed in the subsequent chapters of this thesis.

Travel behaviour analysis carries significant importance in demand forecasting and policymaking. Smart mobility is prevailing these years with an aim to offer people easier travel, and many new smart mobility services (e.g. HSR-air intermodality, ride-sharing, urban air mobility) have appeared or are waiting to be launched in the market. Theoretical studies on the impact of new smart mobility services on vehicle (aircraft) control, traffic control, pricing, and environment etc. have been widely conducted at an aggregate level. These studies can provide valuable insights to transport practitioners in terms of operation optimisation.

Nevertheless, since many of these new travel modes are still quite new to the general public or are still under development, empirical analyses at a disaggregate level in the new context of smart mobility on mode choice behaviour are still quite limited. For instance, choice behaviour at the initial stage of a diffusion process requires exploration. In particular, the role of underlying psychological constructs requires attention when a new mode enters the market. At this stage, inertia and resistance to change may also influence the willingness to adopt the new mode. The adoption behaviour can also be relevant to risk perception and risk-taking tendencies as little external information is available to assist decision-making. Moreover, adoption of the new mode can be partly driven by the intrinsic desire for innovation and variety, which could be positively corre-



lated with risk-taking tendencies (Trijp et al., 1996; Zuckerman and Kuhlman, 2000). This further relates to the persistence of such desire as the innovation will gradually become less novel for those early adopters. Longitudinal RP data is essential to examine whether those early adopters would be consistently choosing the new mode over time. Also, the adoption behaviour of imitators during the diffusion process is worth investigation. The gaps need to be bridged in terms of understanding how social influences accumulate over time and to what extent do social influences affect adoption for imitating decision-makers.

The specific gaps listed below are what accounted for in this thesis, all of which stem from travel behaviour from a disaggregate perspective in the context where new smart mobility services come into play.

- **Gap G1: Novelty-seeking aspect of variety-seeking**

When a new product enters the market, be it food or smart mobility service, there is heterogeneity across individuals in respect of their tendencies to adopt this new product, which influences different individuals' choice behaviour differently. Some studies have modelled technology adoption behaviour at an aggregate level over a relatively long time span based on the adoption and diffusion theory (Bass, 1969; Kalish, 1985), where adoption is affected by social influence from previous adopters, leaving individual novelty-seeking behaviour which is intrinsically motivated lacking discussion.<sup>9</sup> In contrast, novelty-seeking has been intensively analysed from a psychological perspective using various psychometric scales to measure individuals' novelty-seeking tendencies. Nevertheless, there exists a gap in measuring novelty-seeking tendencies at an individual level and analysing their impact on choice behaviour in the transport realm.<sup>10</sup> Bridging this gap can help transport practitioners and policymakers to better understand the emerging market.

- **Gap G2: Alternation aspect of variety-seeking**

When there are many different alternatives available to be chosen, for example among different travel modes or juice brands, different individuals seek variety of choices to different extents. That is, while some people prefer to alternate their choices among a wider set more frequently, others are more inclined to avoid changes and remain to their habitual selection. Improving

---

<sup>9</sup>El Zarwi et al. (2017) combined discrete choice modelling techniques with technology adoption model which is able to probabilistically segment respondents into early adopters, imitators and non-adopters through a disaggregate manner.

<sup>10</sup>Many tourism studies have examined the impact of novelty-seeking tendencies on choices (e.g. Assaker and Hallak 2013; Jang and Feng 2007; Lee and Crompton 1992).

the understanding of alternation is critical to identifying loyal customers and spotting the need for expanding options for selection in the market. However, similarly to the novelty-seeking aspect, research attention on the alternation aspect also mainly comes from consumer marketing, and very little effort has been carried out in travel behaviour analyses. Besides, the alternation characteristics can usually be reflected in longitudinal data (e.g. RP data) which records individuals' choices at different time points. However, whether alternation effect is also present within a choice experiment (e.g. SC data) which is conducted in a single setting is not clear.

- **Gap G3: Attribute importance under uncertainty**

Under RUM theory and compensatory assumption, it is considered that people make choices amongst different alternatives based on the trade-offs among various level-of-service attributes that profile the alternatives. Nevertheless, the entry of a new product to the market brings about uncertainty in the way that individuals perceive the importance of new attributes. In order to have better a understanding of the mode choice behaviour and the roles that attributes play in decision making when new modes are introduced, it is imperative to exploit more behavioural information from each respondent. Adopting multiple types of preference elicitation methods and jointly estimating different types of data can be beneficial.

As mentioned in section 1.2, some studies have jointly used multiple preference elicitation methods to improve the understanding of attribute importance under this uncertainty. However, BWS data has not been used together with the conventional SC data for this purpose, whereas BWS data could provide analysts with useful information on attribute processing. Moreover, whether different approaches reveal attribute importance in a consistent way is a crucial question to answer. This is because relatively high consistency implies an opportunity for data merge as well as the reliability of different approaches in retrieving attribute importance. Therefore, more work on combining BWS data and SC data is needed to address attribute importance under uncertainty caused by the introduction of new travel modes.

## 1.4 Data used in this thesis

Since China has the longest HSR network worldwide and has been promoting the HSR-air intermodality practice more recently, and the U.S. is pioneering in

#### 1.4. Data used in this thesis

the field of urban air mobility, this thesis makes use of HSR-air intermodality data collected in China and air taxi data obtained in the U.S.

In order to fill in the research gaps identified in section 1.3, individual-level behavioural data is required. Given that China’s HSR-air intermodal service is still in its initial stage and air taxi service has not been launched yet in the U.S., it is difficult to collect RP data or use ubiquitous data (e.g. mobile phone data, smart card data), despite their advantages and growing popularity in the field of choice modelling. Therefore, this thesis relies on SP data, including SC data which collects individuals’ preferences through hypothetical choice scenarios. Table 1.2 summarises the major types of data used in each of the subsequent three chapters.

**Table 1.2:** Data used in this thesis

Chapter	Research context	New mode	Data type	Gap	Factors investigated
Ch 2	Intermodal mobility	Integrated HSR-air	SC+rating	G1	Novelty-seeking
Ch 3	Shared mobility	Air taxi	SC+rating	G1+G2	Novelty-seeking+Alternation
Ch 4	Intermodal mobility	Integrated HSR-air	SC+BWS1+BWS2	G3	Attribute importance

For mode choice analyses in the context of HSR-air intermodal mobility, SC data was collected in Pudong International Airport in Shanghai of China in January 2017. The location was chosen in Shanghai as it is the city that first introduced HSR-air intermodal service in China. Although such intermodal mobility service was not available at Pudong International Airport but available at another airport in Shanghai (i.e. Hongqiao International Airport) during the survey period, much more long-haul flight passengers who needed to transfer from/to HSR travel could be found at Pudong International Airport.<sup>11</sup> The SC survey was generated by the author of this thesis through *D*-efficient experimental design which was tailored for the research context with an aim to achieve a balance between being realistic and allowing for adequate variations in trade-offs. The data collection was conducted solely by the author through face-to-face survey, which greatly explains the relatively small sample size (i.e. 123 valid respondents). Nevertheless, sufficient behavioural data was obtained given each respondent completed 8 stated choice tasks in the SC survey. The detailed information about the experimental design for this SC survey is shown in Appendix A.3.

Additionally, in order to extract more behavioural information per individual to study the attribute processing under uncertainty without adding too much cognitive burden, respondents were required to complete alternative preference-retrieving surveys in the context of HSR-air intermodality. As mentioned earlier,

<sup>11</sup>For details of the regional context, please see Chapter 2.

BWS surveys are getting increasingly popular for preference analyses, thus two additional BWS surveys were included after the SC survey, containing 7 tasks in a BWS1 survey and 8 tasks in a BWS2 survey. The BWS1 survey was generated through BIBD design, of which details are shown in Appendix B.1. The BWS2 survey was derived directly from the profiles defined through the SC survey.

Regarding mode choice analysis in the context of shared mobility, the data was provided by Uber and Resource Systems Group Inc., who collected the data in 2018 in Los Angeles and Dallas-Fort Worth areas of the U.S. from an online panel and Uber customer list.<sup>12</sup> The SC survey, which was also created through a *D*-efficient experimental design, presented each respondent with 10 hypothetical stated choice tasks.<sup>13</sup> The choice sets included the upcoming air taxi alternative<sup>14</sup>, as well as other existing ground-based shared mobility services (i.e. UberX, UberPOOL), and other conventional modes on land. Consequently, a large number of respondents were approached, and the responses of 2419 individuals were used in the analysis.

Apart from the aforementioned major datasets used in this thesis, responses towards some attitudinal statements were also gathered in the form of Likert scale in each research context. These attitudinal questions are related to latent constructs like variety-seeking, resistance to change, etc. Besides, information about travel experience and personal socio-demographic characteristics was also collected in each research context. The attitudinal rating tasks are shown in Chapter 2 for the study of intermodal mobility and in Chapter 3 for the shared mobility analysis.

## 1.5 Objectives and implementation

The emergence of HSR-air intermodality service and the upcoming air taxi service provides a good opportunity to address the three research gaps identified in section 1.3. By making use of the data described in section 1.4, this section outlines the detailed research objectives and the plans to achieve them.

---

<sup>12</sup>The University of Leeds, UK was provided with anonymized data by Uber Technologies, Inc. ("Uber"). Neither the University of Leeds nor the authors received funding or financial support from Uber, and the views, opinions, and conclusions expressed in this article are those of the authors and do not constitute any representation of Uber.

<sup>13</sup>This SC survey design was conducted by Uber and was not within our control.

<sup>14</sup>Uber's innovative air taxi service (UberAIR) is to be launched in 2023. Its spearhead helicopter service has been launched between John F. Kennedy Airport and Midtown Manhattan in the U.S. in July 2019. Eventually, UberAIR will be served by drones.

- **Objective O1: Developing a quantitative way to analyse the impact of novelty-seeking aspect of variety-seeking on individual mode choice behaviour**

**Implementation I1:**

- Creating a psychometric measurement (e.g. scale) on variety-seeking<sup>15</sup> based on existing relevant scales and adapt it into the transport context.
  - Designing a SC survey to mimic the real-world market environment and collect people’s preferences.
  - Establishing an ICLV model and analysing the impact of novelty-seeking on preferences towards different mode alternatives within RUM-based choice modelling framework.
- **Objective O2: Developing a quantitative approach to account for the impact of alternation aspect of variety-seeking on individual mode choice behaviour**

**Implementation I2:**

- Creating a psychometric measurement on variety-seeking based on existing relevant scales and adapt it into the transport context.
  - Designing a SC survey to mimic the real-world market environment and collect people’s preferences.
  - Establishing a LC model to probabilistically segment respondents into different classes as a function of the latent variable of variety-seeking, and meanwhile accommodating the two aspects of variety-seeking simultaneously within the same modelling framework.
- **Objective O3: Assessing attribute importance through different SP methods and examining the consistency of these methods in revealing individuals’ perception of attribute importance in situations where individuals experience uncertainty caused by the introduction of the new and unfamiliar**

---

<sup>15</sup>As mentioned in section 1.2, there is no need to differentiate between the novelty-seeking aspect and alternation aspect of variety-seeking.

**Implementation I3:**

- Designing a BWS1 survey to ask respondents to directly reveal their perception of importance towards different attributes.
- Designing a BWS2 survey to let respondents evaluate amongst a set of attribute levels, from which attribute importance could be inferred.
- Designing a SC survey to mimic the choices among different alternatives in the real-world market environment, where attribute importance also plays a critical role in decision-making.
- Establishing an ICLV model to combine all the three types of data together by treating attribute importance as a latent variable that enters into the utility functions of all the three types of data.

## 1.6 Thesis outline and contributions

Since this thesis is submitted in the alternative format by publications, the subsequent three chapters present the three papers composed during the PhD study period before a final concluding chapter. The main research tasks and original contributions of each paper are summarised in this section.

**Chapter 2** examines the impact of variety-seeking on mode choice behaviour in the context of HSR-air intermodal mobility. This study aims at realising the first research objective as stated in section 1.5. As a standard part in analysis, this study identifies the impact of various level-of-service attributes in this context, analyses value of travel time for different types of time component across different categories of respondents and calculates willingness to pay for certain “good attributes”. This chapter focuses on the novelty-seeking aspect of variety-seeking (i.e. the inclination to adopt new modes). By introducing a latent variable of variety-seeking and interacting it with the error component of alternatives within a mixed multinomial logit choice model, part of preference heterogeneity across individuals, i.e. inter-individual preference heterogeneity, is explained by the novelty-seeking effect of variety-seeking. The modelling results suggest that novelty seekers would be more likely to choose the newly-introduced integrated HSR-air service.

**Chapter 3** analyses how variety-seeking affects mode choice behaviour in the context of shared mobility, where different ground-based shared mobility services, as well as the to-be-launched air taxi service (UberAIR), are incorporated. This work targets the second research objective identified in section 1.5. Unlike Chapter 2, this work not only considers the novelty-seeking effect but also accounts

for the alternation aspect of variety-seeking (i.e. the inclination to vary one’s behaviour regularly by selecting different modes continuously). An innovative two-layer latent class model integrated with a latent variable on variety-seeking is proposed. This model postulates that variety-seeking can be driven/reflected by both the novelty-seeking aspect and alternation aspect, i.e. stronger variety-seeking tendencies are not only associated with higher tendencies to adopt the new air taxi service but also might relate to more varied choices in the course of completing the SC tasks. Specifically, the alternation effect is accommodated through the unstableness in preferences across choice tasks, i.e. intra-individual preference heterogeneity. More precisely, this new model is realised by replacing the two layers of continuous distributions in the mixed multinomial logit model proposed by [Hess and Rose \(2009\)](#) with two layers of discrete distributions in the latent class model, and by associating the latent variable of variety-seeking with the membership of classes. In this model, individuals could be probabilistically classified into novelty-seekers and novelty-avoiders first and then have a probability to be affected by the alternation effect (i.e. exhibit intra-individual preference heterogeneity). This can markedly reduce the computational burden caused by taking a large number of random draws and can contribute to better market segmentation. The findings of the new model 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 intra-individual preference heterogeneity than alternation avoiders.

**Chapter 4** is also set in the context where HSR-air intermodal service is involved and it attempts to address the third research objective identified in section 1.5. This work emphasises on exploring the consistency of different types of data (i.e. SC data, BWS1 data and BWS2 data) in revealing attribute importance in mode choice behaviour at an individual level, and utilising the additional behavioural information gained from BWS data to improve the explanation of choices and the role of attributes in the presence of the new mode. Unlike existing comparisons in retrieving attribute importance between SC data and BWS1/2 data which are conducted at the sample, this work carries out comparisons between SC data and BWS1/2 data at the individual level through data synthesis. That is, all the three types of data are combined through the common linkage, i.e. attribute importance, within a single ICLV model framework, such that all the three types of data can be jointly estimated with their correlations captured. In this model, each attribute is associated with a latent variable of attribute importance, which enters into the “utility” functions for all the three types of data,

such that the measurement error and endogeneity bias can be avoided. Few studies have estimated SC, BWS1 and BWS2 data within a same discrete choice modelling framework simultaneously or investigated the consistency among different types of data in revealing the importance of attributes at the individual level. In this sense, this work makes a contribution to merging these three types of data and examining their consistency. The modelling results show that latent attribute importance can effectively link different types of data and there is acceptable consistency is found especially for non-cost attributes, whereas the study does not find a one-to-on relationship between the different types of data. Nevertheless, it is illustrated that the additional behavioural information obtained from BWS data can be exploited to contribute to better understandings of choices in SC data.



## References

- Adamsen, J.M., Rundle-Thiele, S., Whitty, J.A., 2013. Best-worst scaling... reflections on presentation, analysis, and lessons learnt from case 3 bws experiments. *Market & Social Research* 21, 9.
- Allard, R.F., Moura, F., 2016. The incorporation of passenger connectivity and intermodal considerations in intercity transport planning. *Transport Reviews* 36, 251–277.
- Assaker, G., Hallak, R., 2013. Moderating effects of tourists' novelty-seeking tendencies on destination image, visitor satisfaction, and short-and long-term revisit intentions. *Journal of Travel Research* 52, 600–613.
- Auger, P., Devinney, T.M., Louviere, J.J., 2007. Using best-worst scaling methodology to investigate consumer ethical beliefs across countries. *Journal of Business Ethics* 70, 299–326.
- Bass, F.M., 1969. A new product growth for model consumer durables. *Management science* 15, 215–227.
- Baumgartner, H., Steenkamp, J.B.E., 1996. Exploratory consumer buying behavior: Conceptualization and measurement. *International journal of Research in marketing* 13, 121–137.
- Becker, F., Danaf, M., Song, X., Atasoy, B., Ben-Akiva, M., 2018. Bayesian estimator for logit mixtures with inter-and intra-consumer heterogeneity. *Transportation Research Part B: Methodological* 117, 1–17.
- Ben-Akiva, M., McFadden, D., Train, K., Walker, J., Bhat, C., Bierlaire, M., Bolduc, D., Boersch-Supan, A., Brownstone, D., Bunch, D.S., et al., 2002a. Hybrid choice models: progress and challenges. *Marketing Letters* 13, 163–175.
- Ben-Akiva, M., McFadden, D., Train, K., et al., 2019. Foundations of stated preference elicitation: Consumer behavior and choice-based conjoint analysis. *Foundations and Trends® in Econometrics* 10, 1–144.
- Ben-Akiva, M., Walker, J., Bernardino, A.T., Gopinath, D.A., Morikawa, T., Polydoropoulou, A., 2002b. Integration of choice and latent variable models. *Perpetual motion: Travel behaviour research opportunities and application challenges* , 431–470.
- Benevolo, C., Dameri, R.P., D'Auria, B., 2016. Smart mobility in smart city, in: *Empowering Organizations*. Springer, pp. 13–28.

## References

- Bhat, C.R., 1998. Accommodating variations in responsiveness to level-of-service measures in travel mode choice modeling. *Transportation Research Part A: Policy and Practice* 32, 495–507.
- Borgers, A., Van Der Heijden, R., Timmermans, H., 1989. A variety seeking model of spatial choice-behaviour. *Environment and Planning A* 21, 1037–1048.
- Brida, J.G., Martín, J.C., Román, C., Scuderi, R., 2017. Air and hst multimodal products. a segmentation analysis for policy makers. *Networks and Spatial Economics* 17, 911–934.
- Burghouwt, G., Redondi, R., 2013. Connectivity in air transport networks: an assessment of models and applications. *Journal of Transport Economics and Policy (JTEP)* 47, 35–53.
- Busemeyer, J.R., Townsend, J.T., 1993. Decision field theory: a dynamic-cognitive approach to decision making in an uncertain environment. *Psychological review* 100, 432.
- Caragliu, A., Del Bo, C., Nijkamp, P., 2011. Smart cities in europe. *Journal of urban technology* 18, 65–82.
- Chen, X., Zheng, H., Wang, Z., Chen, X., 2018. Exploring impacts of on-demand ridesplitting on mobility via real-world ridesourcing data and questionnaires. *Transportation* , 1–21.
- Chen, X.M., Zahiri, M., Zhang, S., 2017. Understanding ridesplitting behavior of on-demand ride services: An ensemble learning approach. *Transportation Research Part C: Emerging Technologies* 76, 51–70.
- Chiambaretto, P., Baudelaire, C., Lavril, T., 2013. Measuring the willingness-to-pay of air-rail intermodal passengers. *Journal of air transport management* 26, 50–54.
- Chintagunta, P.K., 1998. Inertia and variety seeking in a model of brand-purchase timing. *Marketing Science* 17, 253–270.
- Chorus, C.G., 2010. A new model of random regret minimization. *European Journal of Transport and Infrastructure Research* 10.
- Chorus, C.G., Arentze, T.A., Timmermans, H.J., 2008. A random regret-minimization model of travel choice. *Transportation Research Part B: Methodological* 42, 1–18.

## References

- Cohen, A., Shaheen, S., 2018. Planning for shared mobility.
- Commission of the European Communities, 1993. The Future Development of the Common Transport Policy: A Global Approach to the Construction of a Community Framework for Sustainable Mobility: Communication from the Commission: Document Drawn Up on the Basis COM (92) 494 Final. Office for Official Publications of the European Communities.
- Dekker, T., Hess, S., Brouwer, R., Hofkes, M., 2016. Decision uncertainty in multi-attribute stated preference studies. *Resource and Energy Economics* 43, 57–73.
- Dias, F.F., Lavieri, P.S., Garikapati, V.M., Astroza, S., Pendyala, R.M., Bhat, C.R., 2017. A behavioral choice model of the use of car-sharing and ride-sourcing services. *Transportation* 44, 1307–1323.
- Djavadian, S., Chow, J.Y., 2017. An agent-based day-to-day adjustment process for modeling ‘mobility as a service’ with a two-sided flexible transport market. *Transportation research part B: methodological* 104, 36–57.
- Docherty, I., Marsden, G., Anable, J., 2018. The governance of smart mobility. *Transportation Research Part A: Policy and Practice* 115, 114–125.
- El Zarwi, F., Vij, A., Walker, J.L., 2017. A discrete choice framework for modeling and forecasting the adoption and diffusion of new transportation services. *Transportation Research Part C: Emerging Technologies* 79, 207–223.
- European Commission’s Directorate-General for Mobility and Transport, 2010. LINK Project: Intermodal Passenger Transport in Europe. [http://www.rupprecht-consult.eu/uploads/tx\\_rupprecht/LINK\\_Guidance\\_Brochure.pdf](http://www.rupprecht-consult.eu/uploads/tx_rupprecht/LINK_Guidance_Brochure.pdf).
- Fagnant, D.J., Kockelman, K., 2015. Preparing a nation for autonomous vehicles: opportunities, barriers and policy recommendations. *Transportation Research Part A: Policy and Practice* 77, 167–181.
- Fagnant, D.J., Kockelman, K.M., 2018. Dynamic ride-sharing and fleet sizing for a system of shared autonomous vehicles in austin, texas. *Transportation* 45, 143–158.
- Finn, A., Louviere, J.J., 1992. Determining the appropriate response to evidence of public concern: the case of food safety. *Journal of Public Policy & Marketing* 11, 12–25.

## References

- Flynn, T.N., Louviere, J.J., Peters, T.J., Coast, J., 2007. Best–worst scaling: what it can do for health care research and how to do it. *Journal of health economics* 26, 171–189.
- Flynn, T.N., Louviere, J.J., Peters, T.J., Coast, J., 2008. Estimating preferences for a dermatology consultation using best-worst scaling: comparison of various methods of analysis. *BMC Medical Research Methodology* 8, 76.
- Garau, C., Masala, F., Pinna, F., 2016. Cagliari and smart urban mobility: Analysis and comparison. *Cities* 56, 35–46.
- Gebhardt, L., Krajzewicz, D., Oostendorp, R., Goletz, M., Greger, K., Klötzke, M., Wagner, P., Heinrichs, D., 2016. Intermodal urban mobility: users, uses, and use cases. *Transportation Research Procedia* 14, 1183–1192.
- Givon, M., 1984. Variety seeking through brand switching. *Marketing Science* 3, 1–22.
- Givoni, M., Banister, D., 2006. Airline and railway integration. *Transport policy* 13, 386–397.
- Givoni, M., Banister, D., 2007. Role of the railways in the future of air transport. *Transportation planning and technology* 30, 95–112.
- Goyal, R., 2018. Urban air mobility (uam) market study .
- Greene, W.H., Hensher, D.A., 2003. A latent class model for discrete choice analysis: contrasts with mixed logit. *Transportation Research Part B: Methodological* 37, 681–698.
- Greene, W.H., Hensher, D.A., 2013. Revealing additional dimensions of preference heterogeneity in a latent class mixed multinomial logit model. *Applied Economics* 45, 1897–1902.
- Ha, J., Jang, S.S., 2013. Variety seeking in restaurant choice and its drivers. *International Journal of Hospitality Management* 32, 155–168.
- Hanani, H., 1975. Balanced incomplete block designs and related designs. *Discrete Mathematics* 11, 255–369.
- Hansen, W.G., 1959. How accessibility shapes land use. *Journal of the American Institute of planners* 25, 73–76.

- He, F., Wang, X., Lin, X., Tang, X., 2018. Pricing and penalty/compensation strategies of a taxi-hailing platform. *Transportation Research Part C: Emerging Technologies* 86, 263–279.
- Hensher, D.A., 1994. Stated preference analysis of travel choices: the state of practice. *Transportation* 21, 107–133.
- Hensher, D.A., 2006. How do respondents process stated choice experiments? attribute consideration under varying information load. *Journal of applied econometrics* 21, 861–878.
- Hensher, D.A., 2010. Attribute processing, heuristics and preference construction in choice analysis, in: *Choice Modelling: The State-of-the-art and The State-of-practice: Proceedings from the Inaugural International Choice Modelling Conference*, Emerald Group Publishing Limited. pp. 35–69.
- Hensher, D.A., Rose, J.M., 2009. Simplifying choice through attribute preservation or non-attendance: implications for willingness to pay. *Transportation Research Part E: Logistics and Transportation Review* 45, 583–590.
- Hess, S., 2014. 14 latent class structures: taste heterogeneity and beyond, in: *Handbook of choice modelling*. Edward Elgar Publishing Cheltenham, pp. 311–329.
- Hess, S., Giergiczny, M., 2015. Intra-respondent heterogeneity in a stated choice survey on wetland conservation in belarus: first steps towards creating a link with uncertainty in contingent valuation. *Environmental and Resource Economics* 60, 327–347.
- Hess, S., Hensher, D.A., 2013. Making use of respondent reported processing information to understand attribute importance: a latent variable scaling approach. *Transportation* 40, 397–412.
- Hess, S., Rose, J.M., 2009. Allowing for intra-respondent variations in coefficients estimated on repeated choice data. *Transportation Research Part B: Methodological* 43, 708–719.
- Hess, S., Train, K.E., 2011. Recovery of inter-and intra-personal heterogeneity using mixed logit models. *Transportation Research Part B: Methodological* 45, 973–990.
- Jang, S.S., Feng, R., 2007. Temporal destination revisit intention: The effects of novelty seeking and satisfaction. *Tourism management* 28, 580–590.

## References

- Jin, S.T., Kong, H., Wu, R., Sui, D.Z., 2018. Ridesourcing, the sharing economy, and the future of cities. *Cities* 76, 96–104.
- Kahn, B.E., Meyer, R.J., 1991. Consumer multiattribute judgments under attribute-weight uncertainty. *Journal of Consumer Research* 17, 508–522.
- Kalish, S., 1985. A new product adoption model with price, advertising, and uncertainty. *Management science* 31, 1569–1585.
- Ke, J., Zheng, H., Yang, H., Chen, X.M., 2017. Short-term forecasting of passenger demand under on-demand ride services: A spatio-temporal deep learning approach. *Transportation Research Part C: Emerging Technologies* 85, 591–608.
- Krueger, R., Rashidi, T.H., Rose, J.M., 2016. Preferences for shared autonomous vehicles. *Transportation research part C: emerging technologies* 69, 343–355.
- Le Vine, S., Polak, J., 2015. Introduction to special issue: new directions in shared-mobility research. *Transportation* 42, 407–411.
- Lee, T.H., Crompton, J., 1992. Measuring novelty seeking in tourism. *Annals of tourism research* 19, 732–751.
- Li, Z.C., Sheng, D., 2016. Forecasting passenger travel demand for air and high-speed rail integration service: A case study of beijing-guangzhou corridor, china. *Transportation Research Part A: Policy and Practice* 94, 397–410.
- Lombardi, P., Giordano, S., Farouh, H., Yousef, W., 2012. Modelling the smart city performance. *Innovation: The European Journal of Social Science Research* 25, 137–149.
- Louviere, J., Lings, I., Islam, T., Gudergan, S., Flynn, T., 2013. An introduction to the application of (case 1) best–worst scaling in marketing research. *International Journal of Research in Marketing* 30, 292–303.
- Louviere, J.J., Flynn, T.N., Marley, A.A.J., 2015. *Best-worst scaling: Theory, methods and applications*. Cambridge University Press.
- Louviere, J.J., Hensher, D.A., Swait, J.D., 2000. *Stated choice methods: analysis and applications*. Cambridge university press.
- Lyons, G., 2018. Getting smart about urban mobility—aligning the paradigms of smart and sustainable. *Transportation Research Part A: Policy and Practice* 115, 4–14.

- Marley, A., Pihlens, D., 2012. Models of best–worst choice and ranking among multiattribute options (profiles). *Journal of Mathematical Psychology* 56, 24–34.
- Marley, A.A., Louviere, J.J., 2005. Some probabilistic models of best, worst, and best–worst choices. *Journal of Mathematical Psychology* 49, 464–480.
- Marti, J., 2012. A best–worst scaling survey of adolescents’ level of concern for health and non-health consequences of smoking. *Social Science & Medicine* 75, 87–97.
- Martín, J.C., Román, C., 2013. Wtp for the integration between the hsr and air transport at madrid barajas airport, in: *International Choice Modelling Conference*, University of Sydney, Australia.
- McAlister, L., Pessemier, E., 1982. Variety seeking behavior: An interdisciplinary review. *Journal of Consumer research* 9, 311–322.
- McFadden, D., 2001. Economic choices. *American economic review* 91, 351–378.
- McFadden, D., et al., 1973. Conditional logit analysis of qualitative choice behavior .
- Pearson, P.H., 1970. Relationships between global and specified measures of novelty seeking. *Journal of Consulting and Clinical Psychology* 34, 199.
- Pessemier, E., Handelsman, M., 1984. Temporal variety in consumer behavior. *Journal of Marketing Research* 21, 435–444.
- Pessemier, E.A., 1985. Varied individual behavior: some theories, measurement methods and models. *Multivariate Behavioral Research* 20, 69–94.
- Rasulkhani, S., Chow, J.Y., 2019. Route-cost-assignment with joint user and operator behavior as a many-to-one stable matching assignment game. *Transportation Research Part B: Methodological* 124, 60–81.
- Rieser-Schüssler, N., Axhausen, K.W., 2012. Investigating the influence of environmentalism and variety seeking on mode choice. *Transportation Research Record* 2322, 31–41.
- Rogers, E.M., 1976. New product adoption and diffusion. *Journal of consumer Research* 2, 290–301.
- Rogers, E.M., 2010. *Diffusion of innovations*. Simon and Schuster.

## References

- Román, C., Martín, J.C., 2014. Integration of hsr and air transport: Understanding passengers' preferences. *Transportation Research Part E: Logistics and Transportation Review* 71, 129–141.
- Sauter-Servaes, T., Nash, A., 2009. Increasing rail demand by improving multimodal information and ticketing: Results of the night & flight case study. *Transportation Research Record* 2117, 7–13.
- Shaheen, S., Chan, N., 2016. Mobility and the sharing economy: Potential to facilitate the first-and last-mile public transit connections. *Built Environment* 42, 573–588.
- Shaheen, S., Cohen, A., 2019. Shared ride services in north america: definitions, impacts, and the future of pooling. *Transport reviews* 39, 427–442.
- Shaheen, S., Cohen, A., Zohdy, I., 2016. Shared mobility: current practices and guiding principles. Technical Report.
- Shen, J., 2009. Latent class model or mixed logit model? a comparison by transport mode choice data. *Applied Economics* 41, 2915–2924.
- Software, S., 2013. The maxdiff system technical paper.
- Stubbs, J., Jegede, F., 1998. The integration of rail and air transport in britain. *Journal of transport Geography* 6, 53–67.
- Train, K.E., 2009. *Discrete choice methods with simulation*. Cambridge university press.
- Trijp, H.C.V., Hoyer, W.D., Inman, J.J., 1996. Why switch? product category-level explanations for true variety-seeking behavior. *Journal of marketing research* 33, 281–292.
- Tversky, A., 1972. Elimination by aspects: A theory of choice. *Psychological review* 79, 281.
- Van Trijp, H.C., Steenkamp, J.B.E., 1992. Consumers' variety seeking tendency with respect to foods: measurement and managerial implications. *European Review of Agricultural Economics* 19, 181–195.
- Vespermann, J., Wald, A., 2011. Intermodal integration in air transportation: status quo, motives and future developments. *Journal of Transport Geography* 19, 1187–1197.



## References

- Vij, A., Carrel, A., Walker, J.L., 2013. Incorporating the influence of latent modal preferences on travel mode choice behavior. *Transportation Research Part A: Policy and Practice* 54, 164–178.
- Walker, J., Ben-Akiva, M., 2002. Generalized random utility model. *Mathematical social sciences* 43, 303–343.
- Willing, C., Brandt, T., Neumann, D., 2017. Intermodal mobility. *Business & Information Systems Engineering* 59, 173–179.
- Wills, T.A., Vaccaro, D., McNamara, G., 1994. Novelty seeking, risk taking, and related constructs as predictors of adolescent substance use: an application of cloning theory. *Journal of substance abuse* 6, 1–20.
- Zanin, M., Herranz, R., Ladousse, S., 2012. Environmental benefits of air–rail intermodality: The example of madrid barajas. *Transportation Research Part E: Logistics and Transportation Review* 48, 1056–1063.
- Zawieska, J., Pieriegud, J., 2018. Smart city as a tool for sustainable mobility and transport decarbonisation. *Transport Policy* 63, 39–50.
- Zha, L., Yin, Y., Du, Y., 2017. Surge pricing and labor supply in the ride-sourcing market. *Transportation research procedia* 23, 2–21.
- Zha, L., Yin, Y., Xu, Z., 2018. Geometric matching and spatial pricing in ride-sourcing markets. *Transportation Research Part C: Emerging Technologies* 92, 58–75.
- Zha, L., Yin, Y., Yang, H., 2016. Economic analysis of ride-sourcing markets. *Transportation Research Part C: Emerging Technologies* 71, 249–266.
- Zhang, A., Wan, Y., Yang, H., 2019. Impacts of high-speed rail on airlines, airports and regional economies: A survey of recent research. *Transport Policy* .
- Zuckerman, M., Kuhlman, D.M., 2000. Personality and risk-taking: common bisocial factors. *Journal of personality* 68, 999–1029.



## Chapter 2

# Accounting for the impact of variety-seeking: theory and application to HSR-air intermodality in China

Fangqing Song<sup>1</sup>, Stephane Hess<sup>1</sup> & Thijs Dekker<sup>1</sup>

## Abstract

*While variety-seeking has been analysed intensively in consumer marketing, little is known about its impact in the transport world where many novel travel services have emerged in recent years. In this paper, we investigate how variety-seeking could influence intercity travellers' mode choice decisions in the new context of HSR (high-speed rail)-air intermodality in China. The study is based on data collected in Shanghai, including responses to stated choice tasks and attitudinal statements on variety-seeking. An integrated choice and latent variable (ICLV) model is proposed with a view to provide us with a more behaviourally realistic explanation of respondents' choice decisions. The research findings suggest that variety-seeking has different impacts across modes, where variety seekers would be more likely to choose the newly-introduced integrated HSR-air option whereas variety avoiders have a higher propensity to choose car-air or traditional separate HSR-air alternative. Meanwhile, this study also examines the impact of various level-of-service attributes in mode choice behaviour, with results implying that long layover would heavily impair the attractiveness of integrated HSR-air service, and integrated luggage handling service is favourable to attract intermodal passengers while the effect of integrated ticketing system remains ambiguous.*

**Key words:** HSR-air intermodality, stated choice, variety-seeking, mode choice, latent variable, discrete choice model

---

<sup>1</sup>Institute for Transport Studies and Choice Modelling Centre, University of Leeds (UK)

## 2.1 Introduction

### 2.1.1 Research background

In recent years, a growing number of researchers and practitioners have moved away from merely analysing the competition between air and HSR (high-speed rail) to viewing the air-HSR relation from a perspective of intermodality featuring cooperation and complementarity. The European Union has long been promoting the complementarity between the air network and the rail network ([European Commission and Transport, 2011](#)) out of capacity, environmental and financial concerns, with an aim to not only alleviate the congestion at busy airports, but also improve the efficiency of the transport system as a whole. In Europe, while rail links (e.g. conventional rail, light rail, metro) at airports can be found relatively widely, HSR-air integration is mainly operationalised in airports with direct connection to a HSR network which requires a large amount of infrastructure investment and operating costs ([Maffi et al., 2012](#)), among which key examples are the cooperation between Thalys trains and Paris Charles-de-Gaulle Airport as well as between Deutsche Bahn trains and Lufthansa Airline on the Stuttgart-Frankfurt route ([Chiambaretto and Decker, 2012](#); [European Commission, 2010](#)).

China has established the world's largest HSR network, with over 22,000km in total by 2016 ([Ministry of Transport of the People's Republic of China, 2017](#)). An integrated HSR-air service, treating HSR travel as a feeder leg of long-distance air travel and allowing passengers to purchase HSR and flight services together, was first launched by China Eastern Airline in conjunction with the Shanghai Railway Bureau in 2011. HSR-air intermodality emerged in China mainly out of two different reasons. Firstly, HSR-air intermodality is expected to facilitate passengers from non-airport regions to access nearby airports where they can travel to/from a distant place. For example, passengers from many prefecture-level or county-level cities in the Yangtze river delta region can have access to airports in Shanghai through HSR. Secondly, HSR-air intermodality is considered capable of diverting passengers to/from a crowded hub airport to a nearby airport in order to decongest the busy hub airport. For example, passengers to/from Beijing Capital Airport - one of the world's busiest airport - are given the options to use the nearby Tianjin Binhai Airport and Shijiazhuang Zhengding Airport, which are about 150km and 300km away.

### 2.1.2 Research questions

Although more cities begin to participate in HSR-air intermodality in China, the general public are not familiar with the integrated service as reflected by its relatively low passenger flow. Take Shanghai as an example, in 2015, about 8100 passengers chose China Eastern Airline’s integrated HSR-air service which requires transferring at Shanghai (either HSR travel first or air travel first) every month while the monthly average volume of flight passengers, including both inbound and outbound, of two Shanghai airports is 8.27 million. The limited passenger demand might be potentially due to the relatively low level of integration of the current HSR-air intermodal service. To be specific, HSR-air intermodality products in China usually simply increase the time-window between the HSR segment and the air segment to diminish the possibility of fail-on-board due to service delay on either segment, making it less attractive to passengers (Li and Sheng, 2016). Besides, although passengers no longer need to purchase tickets twice for HSR journey and air journey, they are only offered with limited options in terms of airline, departure time, etc., and they are still required to collect train ticket and flight ticket separately. Moreover, as pointed out by a study on China’s HSR-air intermodality (Givoni and Chen, 2017), though the benefit of realising integration between air and HSR has been recognised by China’s policy makers and the integration infrastructure has been implemented in Shanghai, the actual integration level of the service is low, which can be attributed to “the institutional (and cultural) division between air and rail transport and excessive importance attached to the competition between air and rail”.

This suggests that the underlying benefits of HSR-air intermodality in China are still yet to be justified and explored, and also reveals the necessity to analyse passengers’ preferences towards different level-of-service attributes of the HSR-air intermodality and to examine how they affect passengers’ mode choice in the context of HSR-air intermodality. In particular, unlike traditional mode choice studies which treat each mono-mode as an alternative in choice set, transport planners need to examine how passengers would choose among several multi-modes alternatives where direct travel service between the origin and destination is unavailable.

Apart from observable level-of-service attributes, other unobserved factors might also influence passengers’ mode choice behaviour. For example, Bennett et al. (1957) suggested that perception of some emotional experience may affect passengers’ mode choice, such that air travel is considered to be associated with anxiety, while rail travel is associated with feelings like slowness, etc. In the current paper, we particularly examine the impact of the underlying variety-seeking

tendency on mode choice behaviour in the new context of HSR-air intermodality. That the integrated HSR-air service could still be treated as a new option in the intercity market even though it has been in the market for around six years, is largely due to the unfamiliarity with the HSR-air intermodality of the general public in China as well as the relatively low integration level of the integrated HSR-air service at the moment. We conduct variety-seeking analysis with a view to explore whether variety seekers would have a higher propensity to choose the new integrated HSR-air alternative while variety avoiders would be more prone to stick to other long-existing traditional alternatives, such as car-air and air-air and separated HSR-air. It should be noted that this paper only addresses such short-run impact of variety-seeking, therefore neither the mode choice behaviour in the long term after the market becomes fully mature, nor the link between choice preference variability/stability and variety-seeking in stated-preference survey is discussed. To be specific, we explore the measurement of underlying variety-seeking and incorporate such information to the choice model in different ways to enhance the behavioural explanatory power of the model.

The main methodology utilised is an ICLV (integrated choice and latent variable) model based on the framework proposed by [Ben-Akiva et al. \(2002\)](#) as it has become the standard approach to understand the impact of unobserved factors on people's decision-making. Our ICLV model has a random utility by the maximisation (RUM) kernel, where the utilities for the different modes are influenced not just by observable characteristics but also the latent construct of variety-seeking which is also used to explain the responses to a series of attitudinal statements.

In the remaining of the current paper, there are five sections. The next section summarises the studies of relevant literature, which is followed by a section that describes the experiment design and data collection work. The applied methodologies and model specifications are presented in section [2.4](#). Then in section [2.5](#), the estimation results are discussed. In the end, the conclusions drawn in the current research and the shortcomings and research potentials are summarised in section [2.6](#).

## 2.2 Literature review and research contribution

### 2.2.1 HSR-air intermodality analysis

Among the research into HSR-air intermodality, most of the studies focus on estimating the impact of initiating HSR-air intermodality on, for example, environmental benefits, fares, traffic volume and welfare ([Albalade et al., 2015](#);

Dobruszkes and Givoni, 2013; Jiang et al., 2017; Jiang and Zhang, 2014; Xia and Zhang, 2016; Zanin et al., 2012). Other studies identify factors that affect the service level of HSR-air intermodality, such as travel time, travel price, ease of transfer, ease of access/egress, baggage handling system, ticket integration, service reliability, check-in and security-check procedures (Costa, 2012; Vespermann and Wald, 2011). An earlier survey by the International Air Transport Association (2003) suggested that poor connection was considered by passengers as the main barrier to travel by HSR before or after flying.

However, analysis of mode choice behaviour is rather limited, among which the majority can be found in the Spanish context (Brida et al., 2017; Martín and Román, 2013; Román and Martín, 2014). The work of Román and Martín (2014) was based on a stated-choice survey which confronted passengers with choices between air-air alternative and the integrated HSR-air alternative if they needed to travel between the remote Island of Gran Canaria and different cities in mainland Spain. It illustrates through various discrete choice models that different travel time components (connection time in particular) and fare integration are highly valued by passengers while the impact of luggage integration is important only for individuals who check in luggage and travel for leisure purposes.

The first and the only comparable analysis conducted in China is by Li and Sheng (2016) which examined mode choice behaviour and made travel demand forecasts on the Beijing-Guangzhou corridor. Notwithstanding the enlightening and valuable findings, some shortcomings of this research can be identified: 1) attribute levels were fixed and respondents from a same group were faced with one same choice task, which might lead to the weakness of examining the trade-off between different attributes and the potential inaccuracy in modal share forecasting; 2) the choice scenario was specified as choosing from a choice set consisting of direct flight, direct HSR, and integrated HSR-air for a domestic intercity travel, whereas we argue that the trade-off between travel time and travel cost would dominate decision-making in such a scenario, making it difficult to detect the roles of other level of service attributes; 3) the authors acknowledged in that paper the necessity to analyse the impact of travel time reliability due to delay, but did not consider it to avoid survey complexity. Other attributes closely related to integration (e.g. luggage integration, ticket integration) were not accounted for in that paper as they were treated as being unimportant in passengers' decision-making, however our research results demonstrate that this is not necessarily the case. Since national and local governments in China are now putting even more effort to establish integrated HSR-air service in more cities, it is of vital importance to have a greater in-depth understanding on how travellers' mode choice

behaviour is influenced by various level of service attributes in order to improve and better benefit from the integrated HSR-air service. In this regard, this paper differentiates itself from [Li and Sheng \(2016\)](#) by accommodating the shortcomings mentioned above and adopting more flexible and advanced discrete choice models. Specifically, our stated choice survey is obtained through experimental design which allows for variations in attribute levels and excludes direct flight or HSR services, requiring each respondent to complete multiple choice tasks. Moreover, our survey takes into account of those integration-specific attributes such that the choice scenarios set up in our survey are more behaviourally realistic. Our study also takes advantage of the responses to additional attitudinal statements which are predictors of the underlying variety-seeking construct, resulting in richer behavioural insights.

### 2.2.2 Variety-seeking analysis

The notion of variety-seeking comes from research in consumer marketing, where [McAlister and Pessemier \(1982\)](#) first made a comprehensive review on variety-seeking behaviour. Variety-seeking can denote different phenomena. For example, some research treats variety-seeking as the phenomenon of “an individual choosing a different alternative from his or her choice set over time due to the induction of the utility (s)he derives from the change itself, irrespective of the alternative (s)he switches to or from” ([Borgers et al., 1989](#); [Givon, 1984](#)). That is to say the variety-seeking behaviour is more intrinsically motivated rather than extrinsically derived ([Van Trijp et al., 1996](#)). In a recent study of variety-seeking on restaurant choices by [Ha and Jang \(2013\)](#), it is stated that variety-seeking can be defined as an intention to either vary among familiar alternatives (alternation) or to choose a new alternative (novelty seeking) - the current paper is based on the latter.

Variety-seeking has been intensively analysed in consumer marketing and commonly observed in actual data in real life, showing that variety seekers tend to seek diversity and new experiences. [Adamowicz \(1994\)](#) and [Borgers et al. \(1989\)](#) established different dynamic models to measure variety-seeking and accounted for them in recreational site choice behaviour, both using longitudinal data and incorporating previous experience to reflect the role of habit and variety-seeking. Empirical studies on brand switching behaviour demonstrate that the ability to measure consumers’ variety-seeking in a certain product market will bring about a better understanding of brand switching in the market ([Givon, 1984](#); [Van Trijp et al., 1996](#)). It is further concluded by [Legohérel et al. \(2015\)](#), who applied a chi-squared automatic interaction detection (CHAID) segmentation



approach to analyse international travellers' choices of hotels and restaurants, that variety-seeking could be treated as a tool to segment markets and different variety-seeking behaviours require different marketing strategies.

Research into variety-seeking is much more limited in the transport literature. Earlier attempts can be found in [Schüssler and Axhausen \(2011\)](#) and [Rieser-Schüssler and Axhausen \(2012\)](#) on mode choice between car and public transport based on daily travel diary data and self-developed scales, in which variety-seeking was accommodated as a latent variable. Other relevant research includes studies of the impact of inertia on adopting the new alternative which requires a combination of revealed-preference (RP) and stated-preference (SP) data or launching SP surveys twice, i.e. before and after the implementation of the novel facility/ service ([González et al., 2017](#); [Jensen et al., 2013](#)). It has also been suggested that intrinsic personal preference might be a driving factor of choosing a specific alternative ([International Air Transport Association, 2003](#)), and that habit could act as a barrier to the change in mode choice behaviour and breaking old habits can potentially result in mode shift ([Blainey et al., 2012](#); [Thøgersen, 2006](#)).

### 2.2.3 Research contribution

The current paper contributes to the literature in two different aspects. Firstly, it provides more evidence on mode choice behaviour analysis in the context of HSR-air intermodality in China through discrete choice methods. This could deepen policy makers' understanding of the driving factors behind passengers' mode choice and preference heterogeneity across passengers, resulting in higher capability of satisfying customers' needs and improving the integrated service. Secondly, this study extends researchers' knowledge of variety-seeking in the transport realm. This could assist policy makers to better identify potential consumers of the integrated HSR-air service as well as to improve marketing segmentation strategies by drawing upon information of variety-seeking rather than purely relying on the socioeconomic characteristics of passengers alone. Moreover, this analysis could offer insights to the investigation of variety-seeking's impact when other new transport service comes into play in this changing world where innovations keep emerging in recent years (e.g. sharing bicycle, sharing vehicle, automated vehicle).

Our results show that:

1. Different level-of-service attributes impose different impact on utility functions, that value of minor time differs between modes and between travel purposes, connection time between HSR network and aircraft network is

highly valued by passengers, delay protection is more welcomed by passengers who are less familiar with the transfer city, the benefit of integrated ticketing system is perceived ambiguously whereas integrated luggage handling system shows attractiveness to passengers, especially those who travel with more than one piece of check-in luggage.

2. Variety-seeking can be manifested by a series of attitudinal indicators and its tendency varies across respondents.
3. Variety-seeking could explain part of the random taste heterogeneity across respondents, apart from the pure randomness which is irrelevant from the latent variable as well as the systematic taste heterogeneity that is associated with certain observable variables.
4. The impact of variety-seeking on utility differs across alternatives, and people who possess higher (lower) level of variety-seeking tendency, can derive less (more) utility from car-air alternative and traditional separated HSR-air alternative, meanwhile more (less) utility from both air-air alternative and the new integrated HSR-air alternative.
5. Younger people and people with higher income tend to be more willing to seek variety.

## 2.3 Data

### 2.3.1 Regional context

The case study is based on data collected in Shanghai, an important city for both the air network and the HSR network in China. Shanghai has two airports which enjoy large catchment area in the Yangtze River Delta region and it currently takes around 1.5h to travel between them by metro. Hongqiao International Airport mainly provides domestic routes and some short-distance international routes (e.g. to Tokyo/ Seoul). Hongqiao HSR station, which is one of the largest railway station in Asia and the linkage of many HSR lines, enjoys a seamless transfer with Hongqiao International Airport<sup>2</sup>, and constitutes the Hongqiao Integrated Transport Hub (the Hongqiao Hub) with Hongqiao International Airport. Pudong International Airport offers much more international routes and

---

<sup>2</sup>Passengers can walk through a passage linking Hongqiao HSR station and T2 terminal which provides domestic flights, and can take a metro train for one stop to move between Hongqiao HSR train station and the T1 terminal which focuses on international flights at the moment.

wider airline choices; moreover, it is positioned as an International gateway hub that serves a high percentage of transfer passengers and wide catchment area, the capacity of which will continue to be expanded. For example, the recently initiated Pudong International Airport Phase III Expansion Project, involving the construction of an additional satellite concourse facility which will be connected to the existing T1 and T2 terminals, is expected to be completed by 2019 and will support 38 million passengers annually<sup>3</sup>. In addition, according to the Shanghai-Nantong Railway Phase II Plan, a new railway station will be established at Pudong International Airport, which will enable Pudong International Airport to be connected to the HSR network by linking it with the trunk HSR line through a new branch line, thus contributing to the establishment of Pudong Hub in the future.

Although seamless intermodal transfer only takes place at Hongqiao Hub at the moment, a pilot survey at Hongqiao Airport showed a very low rate of successfully approaching transfer passengers, especially cross-border passengers, whom we regard as the main target of integrated HSR-air service. On the contrary, Pudong International Airport can guarantee a much higher probability of intersecting cross-border transfer passengers, who are more capable of interpreting the concept of integrated HSR-air service and the survey tasks. Therefore, we carried out the final survey at Pudong International Airport. In addition, since Pudong International Airport would in the near future evolve into an intermodal hub, it is necessary to understand passengers' perception of intermodal service and their preference towards various level-of-service attributes, such that the results could provide insights to policy makers and transport planners who have interests in promoting the establishment of Pudong Hub. Since we rely on a stated choice survey, in which the choices are actually hypothetical, we are able to look at non-existing modes even when seamless transfer between air and HSR is currently unavailable at Pudong airport. This also makes it possible to examine the impact of different levels of transfer ease (e.g. seamless transfer within Hongqiao or Pudong Hub, transfer between Hongqiao and Pudong) on passengers' mode choice behaviour.

#### 2.3.2 Definition

Based on the definition of passenger intermodality given by the [European Commission's Directorate-General for Mobility and Transport \(2010\)](#), we define HSR-air intermodality as the situation where air and HSR provide an integrated service as one combined journey with a fast and even seamless transfer. It is in detail

---

<sup>3</sup>See Wikipedia. [https://en.wikipedia.org/wiki/Shanghai\\_Pudong\\_International\\_Airport](https://en.wikipedia.org/wiki/Shanghai_Pudong_International_Airport)

described in our case study as a situation where: 1) a passenger is travelling from a nearby domestic origin O to an overseas destination D; 2) direct flights from O to D are unavailable; 3) a passenger from O to D needs to travel via Shanghai; and 4) a passenger can only travel by air between Shanghai and D. We denote the first journey between O and Shanghai as the “minor leg” on which various modes are available, and the second journey between Shanghai and D as the “major leg” where air is the only option. Under such a scenario, HSR constitutes a substantial part of the journey, and serves as a feeder service to airlines on additional spokes from a hub airport, and mode substitution between air and HSR exists on the minor leg (Brida et al., 2017; Givoni and Banister, 2006; Román and Martín, 2014; Xia and Zhang, 2016).

The present study considers the choice scenario of the minor leg coming before the major leg rather than the other way around out of concern that if a passenger is delayed on the first leg, the consequence of missing a long-haul flight would be much more severe than missing a short-distance HSR train on the second leg, especially given the relatively high frequency and low price of HSR service in Shanghai and its catchment area.

### 2.3.3 Questionnaire and respondent sampling

A face-to-face survey was conducted at Pudong International Airport in January 2017. Passengers were approached at random and were then screened to ensure that the majority of them were passengers from/to regions in proximity to Shanghai, i.e. within a distance of 210min by HSR from Shanghai<sup>4</sup>, and where aircraft service is available to Shanghai, such that respondents could have a good understanding of our choice scenarios. The detailed screening process is shown in Appendix A.1.

The survey was divided into five components, collecting data on: 1) current travel information, such as origin, destination, travel purpose and number of check-in luggage; 2) travel experience, such as the frequency of air/ HSR travel in the past two years; 3) responses to stated choice tasks; 4) responses to statements in self-designed scales; 5) socioeconomic characteristics of respondents, including gender, age, employment, education, income and nationality. An example of our questionnaire is presented in Appendix A.4.

During the data collection, the author was on site to ensure participants understand the questions, choice scenarios etc. The questionnaire took 29min on average to complete. We dropped all the responses of participants who did not

---

<sup>4</sup>This threshold is chosen as all the cities served by HSR-air intermodality through Shanghai could reach Shanghai within 210min by HSR when authors designed the survey.

complete the full questionnaire. A final sample of 123 respondents was obtained.<sup>5</sup> The sample size is limited mainly due to the difficulty in intercepting qualified respondents and low response rate to the survey. Besides, the data was collected by the corresponding author on her own through face-to-face interview. We acknowledge the limitation of small size especially when working with complex model specifications. It is, however, not rare to see in literature the adoption of small sample size. For example, [Greene and Hensher \(2013\)](#) estimated a latent class mixed multinomial logit model based on 432 choice observations obtained from 108 respondents. In contrast, our modelling work is based on 984 stated choice observations, since each valid respondent contributes to as much as 8 stated choice observations. Moreover, we have additional attitudinal information to help in better understanding of choice behaviour.

The whole sample are Chinese-speaking passengers, and all but two of them declared possession of the Chinese national identification card. The dominant modes for the feeder journey of the current travel were air (45.1%) and HSR (30.8%), indicating the potential market for a well-developed integrated HSR-air service. [Table 2.1](#) summarises the descriptive statistics of respondents. It can be observed that respondents were relatively evenly distributed between genders. The respondents tended to be young and highly educated. We did not control the proportion of respondents with different socioeconomic characteristics to make the data representative of the real-world population, because our work is an exploratory study on exploring the impact of variety-seeking, and international travellers themselves are not representative of the Chinese population. It is possible that potential correlation exists between variety-seeking and the willingness to respond to our survey. Nevertheless, we think the impact would not be significant, as the last column in [Table 2.3](#) suggests that the median scores towards the attitudinal statements only slightly deviate around 4, which is the centre point of a 7-point Likert scale.

### 2.3.4 Stated choice component

The stated choice component presented respondents with 8 stated choice tasks, each with 4 alternatives, namely car-air, air-air, separated HSR-air and integrated HSR-air, giving a total of 984 choice observations for analysis. Car-air

---

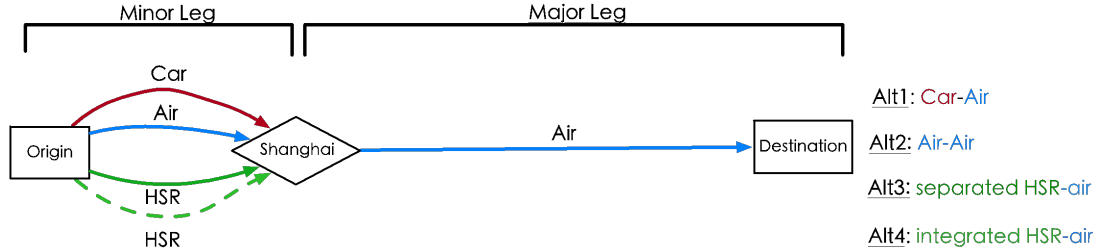
<sup>5</sup>We have also looked into non-trading behaviour and found that 5 out of 123 respondents always chose a same alternative across choice tasks. However, in order to keep behavioural information as much as possible given the limited sample size, we do not exclude these non-traders as we think their behaviour can be accommodated through random error component in our model.

**Table 2.1:** Descriptive statistics of the sample that completed the whole questionnaire

	Levels	Percentage (N=123)
Travel Purpose	Holiday travel	44%
	Family visit	15%
	Business travel	15%
	Study in another city	22%
	Others	6%
Check-in Luggage	0 (none)	11%
	1 (one)	59%
	2 (more than one)	30%
Familiarity with Shanghai city	0 (not at all)	28%
	1 (general)	35%
	2 (very well)	37%
Gender	Female	55%
	Male	45%
Age	<23	31%
	23-35	47%
	36-45	14%
	46-60	7%
	>60	1%
Education	Elementary level or below	1%
	Secondary level	3%
	Graduated from technical school	6%
	Bachelor's degree (Obtained/ reading)	64%
	Master's degree or above (Obtained/ reading)	26%
Annual income <sup>a</sup> (CNY)	<50,000	39%
	50,000-100,000	15%
	100,000-150,000	17%
	150,000-200,000	15%
	200,000-250,000	3%
	>250,000	11%
Employment	Student	38%
	Work for government department or institutions	10%
	Work for company	28%
	Self-employed	11%
	Freelancer	2%
	Retired/ unemployed	1%
	Others	9%

<sup>a</sup>CNY/USD $\approx$ 0.145 during survey period.

means using car on the minor leg and using flight on the major leg; air-air means connecting flights; separated HSR-air refers to the traditional connection which involves purchasing air and HSR tickets separately; integrated HSR-air refers to the new HSR-air intermodal service. Figure 2.1 gives an illustration of the stated choice scenario.



**Fig. 2.1:** Illustration of choice scenarios in SC survey

The alternatives involved in the SC tasks were identified based on the limited existing studies. Our choice scenario differentiates itself from that specified in [Li and Sheng \(2016\)](#), by excluding direct travel options in the choice set, as we argue that trade-offs between travel time and travel cost would dominate decision-making strategy otherwise. In addition, unlike the choice set in [Román and Martín \(2014\)](#), we herein split the “HSR-air” alternative into a separated one and an integrated one. Since the Yangtze River Delta region has a very dense HSR network, many passengers currently buy tickets separately when they need to take a HSR train to reach the airport. Thus, there would be a choice between the traditional separated HSR-air and the new integrated HSR-air when both options are available. We further add a “car-air” alternative based on [Román and Martín \(2014\)](#) as the choice context of our SC tasks relates to origins which are in the catchment of Shanghai and can access Shanghai by air, HSR and car. Hence, we have 4 alternatives in the end.

Stated choice tasks were generated in Ngene ([Metrics, 2012](#)) using a  $D$ -efficient experimental design ([Rose and Bliemer, 2007](#)) which drew prior information from a pilot survey conducted in July 2016 at Hongqiao International Airport. The detailed description of how the attributes were identified is discussed in [Appendix A.2](#), which included three steps, i.e. literature review, best-worst (case 1) pilot survey and SC pilot survey.

Two separate experimental designs generated for the formal SC survey, each with 5 blocks, were produced in order to account for the different distance (i.e. short/ long) on the major leg (and the resulting lower/higher travel cost) while maintaining the available levels of all the other attributes the same in the two designs. Stated choice tasks were presented to respondents in a randomised order to minimise the order effect. A total of 7 attributes were used, not all of which

apply to every alternative. The full list consists of travel time on the minor leg, transfer time, connection time, protection in case of delay on the minor leg, ticket integration, security check and luggage integration, and travel cost <sup>6</sup>. It needs to be noted that travel time on the major leg was not considered in the survey as it would not vary across choice tasks and alternatives. Table 2.2 summarise the alternative, attributes and attribute levels adopted in the experimental designs for our formal SC survey. The details of the experimental designs for the formal SC survey are presented in Appendix A.3.

The sum of transfer time and connection time gives the time intervals between the departure time of the major leg and the arrival time of the minor leg (i.e. layover). Transfer time refers to the moving time between the two legs which in particular takes a value of 0min for a seamless transfer at an intermodal hub; it can also take a value of 90min or 45min, both indicating a movement between two airports, with the former corresponding to the current transfer time by metro and the latter to the reduced transfer time should the potential rapid linkage between Hongqiao Hub and Pudong International Airport is established in the future. Transfer time is fixed at 0min for car in order to reflect its capability of providing door-to-door travel, while it can take a value of 0min as well as other values for any of the other alternatives. It should be noted that when transfer time takes 0min, it refers to a very easy and seamless transfer between the minor leg and the major leg without the need to move between different airports/stations, rather than literally implying instantaneous movement between the two journeys. Besides, although parking availability may affect the actual transfer time, we do not explicitly specify it as its average impact can actually be captured by the alternative-specific constant in our model.

Connection time refers to the time spent on waiting and going through procedures (e.g. check-in, security check), which is fixed to the minimum pre-departure arrival time of 90min for the car-air alternative to reflect the high mobility of accessing the airport by car. Connection time can take five levels for each of the other three alternatives, where the minimum levels are all set to 90min in order to account for the minimum connection time for connecting flights regulated by airlines and the airport. Connection time can take a maximum of 420min/210min/330min for the air-air/separated HSR-air/integrated HSR-air alternative respectively, all of which are determined to ensure the attribute levels for connection time vary within reasonable ranges which can on the one hand

---

<sup>6</sup>For the sake of brevity, the attribute of “travel time on the minor leg” is called as “minor time” for short, the attribute of “protection in case of delay on the minor leg” is shortened as “delay protection”, the attribute of “security check and luggage integration” is referred to as “luggage integration” in the remain of this paper.



allow for adequate variation of attribute levels which is necessary for estimating the attribute’s sensitivity, and on the other hand ensure the viability of attribute levels presented to passengers in the stated choice survey<sup>7</sup>.

Delay protection gives information on how the respondent would be compensated in case that the delay on the minor leg results in missing the flight on the major leg. There are three possible levels for this attribute, which are “no compensation”, “50% off on changing flight”, and “free flight change”, coded in 0, 1, 2, respectively, where the “no compensation” level always applies for the car-air and separated air-HSR alternatives.

Ticket integration describes the integration level of air and HSR ticketing systems, with four different levels, which are “book tickets separately + fixed-time train on the minor leg”, “book tickets together without easy collection + fixed-time train on the minor leg”, “book tickets together with easy collection + fixed-time train on the minor leg”, and “book tickets together with easy collection + flexible-time train on the minor leg”, coded in 0, 1, 2, 3, respectively. What we mean by “easy collection” here is that a passenger only needs to collect tickets one time while “without easy collection” means that a passenger has to collect the ticket for the minor leg and for the major leg separately. Currently, the intermodal HSR-air service frees passengers from booking tickets twice but still requires them to collect the HSR ticket first at train station and then get the boarding pass at the airport, i.e. without easy collection.

Luggage integration refers to how many security checks and luggage check-in are required throughout the travel, with three different levels, which are “no luggage handling integration system + two security checks”, “integrated luggage handling system available + two security checks”, and “integrated luggage handling system + one security check”, coded in 0, 1, 2, respectively. Herein, integrated luggage handling system allows passengers to check in luggage at the origin and collect luggage at the final destination; two security checks infers that both minor and major legs require security checks while one security check means that a security check is only required at the origin. The attributes of ticket integration and luggage integration do not apply for car-air alternative and are kept at the lowest level for separated air-HSR alternative. Figure 2.2 gives an example of stated choice tasks with the items in *italic* being held invariant over tasks.

---

<sup>7</sup>Currently, layover can be as long as over 10h even at an intermodal hub. Thus we tried to achieve a balance between reflecting the reality and ensuring survey efficiency.

**Table 2.2:** Summary of experimental designs for formal SC survey

<b>Attributes</b>	<b>Car-air</b>	<b>Air-air</b>	<b>Separated HSR-air</b>	<b>Integrated HSR-air</b>
Minor Time (min)	180, 210, 240, 270, 300	50, 60, 70, 80, 90	90, 120, 150, 180, 210	90, 120, 150, 180, 210
Connection Time (min)	0	90, 150, 210, 270, 330	0, 30, 60, 90, 120	60, 90, 120, 180, 240
Transfer Time (min)	0	0, 45, 90	0, 45, 90	0, 45, 90
Delay Protection	NA	level 0, level 1, level 2	NA	level 0, level 1, level 2
Ticket Integration	NA	level 2	level 0	level 1, level 2, level 3
Luggage Integration	NA	level 0, level 2	level 0	level 0, level 1, level 2
Travel cost (RMB) [design 1]	1250, 1550, 1850, 2100, 2350	1050, 1350, 1600, 1800, 2000	1150, 1400, 1650, 1900, 2150	1250, 1450, 1700, 2050, 2250
Travel cost (RMB) [design 2]	4250, 4550, 4850, 5100, 5350	4050, 4350, 4600, 4800, 5000	4050, 4350, 4600, 4800, 5000	4250, 4450, 4700, 5050, 5250

**Table 2.3:** Attitudinal statements on variety-seeking

<b>#</b>	<b>Attitudinal statements</b>	<b>Factor</b>	<b>Median score</b>
A1	I am the kind of person who would try new products even if I'm satisfied with my current purchasing	need for variety	5
A2	If I did a lot of flying, I would like to try different airlines as much as I can, instead of flying just one most of the time	need for variety	4
A3	I like to try new routes to familiar destinations	need for variety	5
A4	A lot of the time I feel the urge to buy something really different from the products/ styles I usually get	need for variety	4
A5	I like to explore somewhere new, different or strange nearly every day	need for variety	5
A6	Whenever my life forms a stable routine, I look for ways to change it	need for variety	5
A7	If I like a brand, I rarely switch from it just to try something different	resistance to change	5
A8	I prefer a routine way of life to an unpredictable one full of change	resistance to change	4
A9	Even though certain food products are available in a number of different flavours, I tend to buy the same flavour	resistance to change	4
A10	Often, I feel a bit uncomfortable even about changes that may potentially improve my life	resistance to change	3
A11	I like to do the same old things rather than try new and different ones	resistance to change	3

	Car-air	Air-air	Separated HSR-air	Integrated HSR-air
Travel cost	¥1,250	¥1,050	¥1,150	¥1,250
Minor time	5h	1.5h	2.5h	2.5h
Transfer time	0h	0h	1.5h	1.5h
Connection time	1.5h	4h	1.5h	2.5h
Delay protection	None	Free flight change	None	50% discount on changing flight
Ticket integration	-	<ul style="list-style-type: none"> <li>• <i>Book together</i></li> <li>• <i>Fixed-time flight on minor leg</i></li> <li>• <i>Easy collection</i></li> </ul>	<ul style="list-style-type: none"> <li>• <i>Book separately</i></li> <li>• <i>Fixed-time train on minor leg</i></li> <li>• <i>No easy collection</i></li> </ul>	<ul style="list-style-type: none"> <li>• <i>Book together</i></li> <li>• <i>Fixed-time train on minor leg</i></li> <li>• <i>Easy collection</i></li> </ul>
Security check and luggage integration	-	<ul style="list-style-type: none"> <li>• Two security checks</li> <li>• No integrated luggage handling system</li> </ul>	<ul style="list-style-type: none"> <li>• <i>Two security checks</i></li> <li>• <i>No integrated luggage handling system</i></li> </ul>	<ul style="list-style-type: none"> <li>• One security check</li> <li>• Integrated luggage handling system available</li> </ul>

Fig. 2.2: Example of the stated choice task in the questionnaire

### 2.3.5 Attitudinal statements

Attitudinal statements were used to measure variety-seeking. All statements were recorded in the form of a 7-point Likert scale, ranging from 1 being “strongly disagree” to 7 referring to “strongly agree”. The statements in the formal survey were refined through two pilot surveys as described below.

A pool of 67 initial statements were selected from various literature on variety-seeking, novelty-seeking, personality constructs, risk-taking, exploratory behaviour, arousal seeking and sensation seeking (Baumgartner and Steenkamp, 1996; Hoyle et al., 2002; Raju, 1980; Van Trijp et al., 1996; Van Trijp and Steenkamp, 1992; Weber et al., 2002). A sample of 30 respondents with a transport or psychology background were asked to score them and provide feedback when finished. Statements were then narrowed down to 33 and tailored to the Chinese transport setting, with the inclusion of new items developed by Oreg (2003).

The shortened questionnaire was then generated on the platform of Qualtrics and spread by online link through the Chinese social media app called WeChat. This link was publically accessible, and the respondents were mainly from the Yangtze River Delta Region. This second pilot survey was carried out during November 25-27, 2016, yielding 234 complete responses. Three factors were extracted by factor analysis in SPSS, which could be interpreted as “resistance to change”, “need for variety”, and “need for information”. Item analysis on each derived factor was conducted subsequently, resulting in 15 selected statements. The Cronbach’s Alphas for the three factors are all above 0.6 (i.e. resistance to

change: 0.639, need for variety: 0.701, need for information: 0.614), and each statement has an item-total correlation score between 0.2 and 0.8, which means that the statements are reliable to measure the three factors (Kline, 2015). While the insights from this factor analysis were used in the development of our choice models reported later in this paper, it should be noted that the specification of the latent variables should not be a priori expected to be the same as these factors given that the hybrid model also explains the choices made in the survey.

In the final survey, each respondent was required to score the attitudinal statements of resistance to change and need for variety in Table 2.3, of which A1-A6 related to need for variety and A7-A11 to resistance to change. It is easy to notice that either stronger agreement with statements A1-A6 or stronger disagreement with statements A7-A11 is associated with stronger variety-seeking tendency. Regarding this, statements A1-A6 and A7-A11 measure the same construct, i.e. *variety-seeking*, from opposite ways. Responses to attitudinal statements are shown in Fig. 2.3, where the extreme levels such as 1 “strongly disagree” and 7 “strongly agree” were much less frequently chosen than the others.

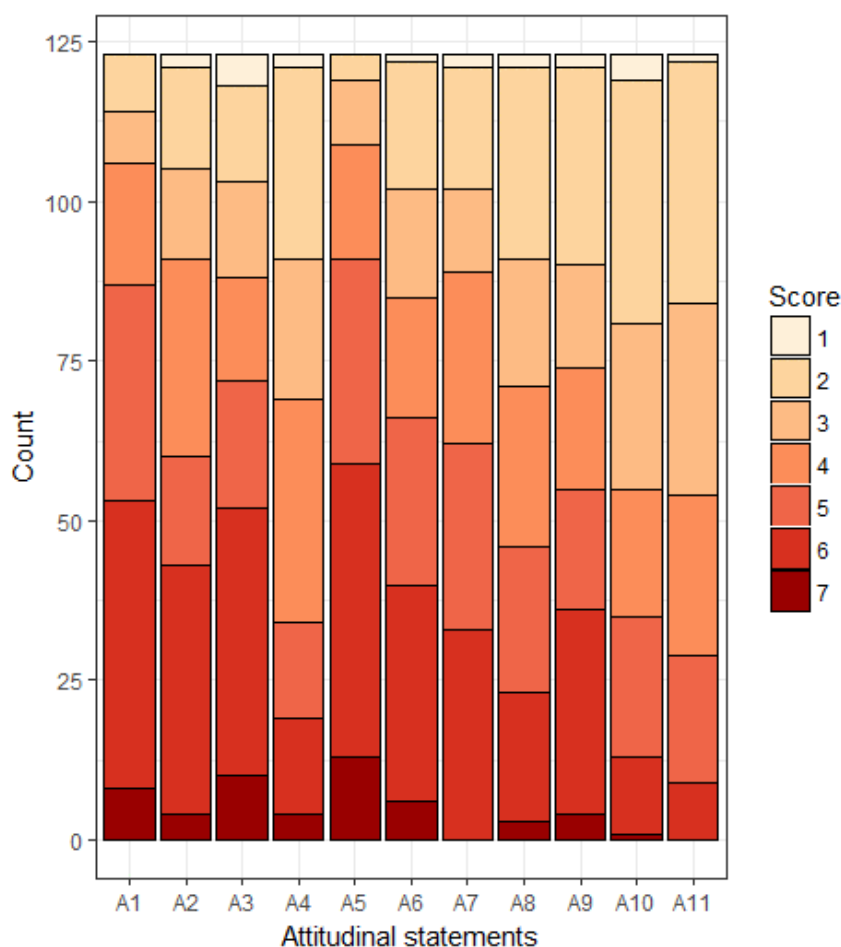


Fig. 2.3: Responses to attitudinal statements

## 2.4 Methodology

In our work, we estimate three types of models which to different extents account for heterogeneity across respondents and the role of variety-seeking in mode choice behaviour in the context of HSR-air intermodality.

### 2.4.1 Multinomial logit model (MNL)

We first develop a MNL model as the base model (McFadden et al., 1973), in which  $U_{int}$  represents the utility obtained from alternative  $i$  in choice task  $t$  for respondent  $n$ .  $U_{int}$  consists of a deterministic portion  $V_{int}$  which is specified to be linear in parameters with an alternative-specific constant (ASC)  $\delta_i$ , and an unobserved error term  $\varepsilon_{int}$  which is independently and identically distributed following a type I extreme value distribution. With  $J$  alternatives in each choice set, one  $\delta$  is fixed to 0 for normalisation while the rest  $J - 1$  alternative-specific constants need to be estimated. With this,  $x_{int}$  is a vector of explanatory variables that represent the attributes shown to respondent  $n$  in choice task  $t$  for alternative  $i$ . Meanwhile,  $\beta$  is a vector that describes the estimated taste coefficients for these attributes. Finally,  $Z_n$  represents a vector of socioeconomic characteristics which is individual specific, and  $\omega_i$  measures their impacts on utility functions, which differs across alternatives. The utility function can thus be written as:

$$U_{int} = V_{int} + \varepsilon_{int} = \delta_i + \beta'x_{int} + \omega_i'Z_n + \varepsilon_{int} \quad (2.1)$$

The probability of alternative  $i$  being chosen out of  $J$  alternatives by respondent  $n$  in choice situation  $t$  is then given by:

$$P_{int} = \frac{e^{V_{int}}}{\sum_{j=1}^J e^{V_{jnt}}} \quad (2.2)$$

### 2.4.2 Mixed multinomial logit model (MMNL)

We next introduce random alternative-specific constant (ASC) to capture the unobserved variation of overall preferences towards each alternative across respondents, i.e. for a given alternative  $i$ ,  $\delta_{in}$  is random across respondents with a mean of  $\mu_{\delta_i}$  and a standard deviation of  $\sigma_{\delta_i}$ , such that  $\delta_{in} = \mu_{\delta_i} + \sigma_{\delta_i}\xi_{in}$ , where  $\xi_{in}$  follows a standard normal distribution over respondents. Again,  $\delta$  for one alternative is fixed to 0 for normalisation. Then the utility function can be given by:

$$U_{int} = V_{int} + \varepsilon_{int} = \mu_{\delta_i} + \sigma_{\delta_i}\xi_{in} + \beta'x_{int} + \omega_i'Z_n + \varepsilon_{int} \quad (2.3)$$

The unconditional choice probability for respondent  $n$  to make a sequence of choices is then specified as:

$$P_n = \int_{\delta_n} \prod_{t=1}^{T_n} P_{nt}(y_{nt}|\delta_n) f(\delta_n|\Omega_\delta) d\delta_n, \quad (2.4)$$

where  $T_n$  is the number of choice tasks given to respondent  $n$ ,  $\delta_n$  is a vector of the random ASC for respondent  $n$  (i.e.  $\delta_n = (\delta_{1n}, \dots, \delta_{Jn})$ ),  $\Omega_\delta$  represents a collection of the corresponding distribution parameters for  $\delta_n$  (i.e.  $\Omega_\delta = (\Omega_{\delta_1}, \dots, \Omega_{\delta_J})$ , where  $\Omega_{\delta_i} = (\mu_{\delta_i}, \sigma_{\delta_i})$ ), and  $f$  gives the density function. We define  $y_{nt}$  to be the alternative chosen by person  $n$  in choice situation  $t$ . As each respondent was required to complete 8 SC tasks in the survey, we estimate the MMNL model in a panel formulation by assuming that tastes vary across respondents but stays constant across choices for each respondent. The log-likelihood ( $LL$ ) function can be written as:

$$LL(y) = \sum_{n=1}^N \ln \left( \int_{\delta_n} \prod_{t=1}^{T_n} P_{nt}(y_{nt}|\delta_n) f(\delta_n|\Omega_\delta) d\delta_n \right), \quad (2.5)$$

where  $N$  denotes the total number of respondents and  $y$  represents the choice outcomes observed by researchers. The resulting  $LL$  function does not have closed-form expression and needs to be approximated through simulation. Suppose we take  $R$  draws from the distribution  $f(\delta_n|\Omega_\delta)$  for each respondent and each random term, then the simulated log-likelihood can be expressed as:

$$SLL(y) = \sum_{n=1}^N \ln \left( \frac{1}{R} \sum_{r=1}^R \prod_{t=1}^{T_n} P_{nt}(y_{nt}|\delta_n^r) \right) \quad (2.6)$$

### 2.4.3 Integrated choice and latent variable model (ICLV)

#### 2.4.3.1 Model Framework

Directly incorporating responses to attitudinal statements as observable explanatory variables potentially leads to measurement error and endogeneity bias (Ashok et al., 2002; Kim et al., 2014). To deal with these issues, the ICLV model has become a commonly used approach to better account for the impact of the unobservable factors by treating them as latent variables. Fig. 2.4 provides an illustration of our model structure which is based on the standard framework proposed in Ben-Akiva et al. (2002). The model consists of two components, which are a choice model and a latent variable model, each including structural equations and measurement equations. Items in rectangular can be directly

observed by researchers and items in ellipse are unobserved. Solid arrows represent structural equations which describe the cause-and-effect relationships, while dashed arrows refer to measurement equations which explain indicators by latent variables or choices by utilities. Consequently, the latent variable model and the choice model are linked through the latent variable which is used to explain both attitudinal indicators in the measurement equations of the latent variable model and utility functions of alternatives in the choice model component.

Under our ICLV structure, utilities are determined by both observable explanatory variables and the latent variable *variety-seeking tendency*, with the latter also being used to explain the corresponding attitudinal indicators. Therefore, the potential issue of endogeneity bias and measurement error could be corrected. Our ICLV model is estimated simultaneously through maximum likelihood estimation which leads to gains in efficiency compared to sequential estimation.

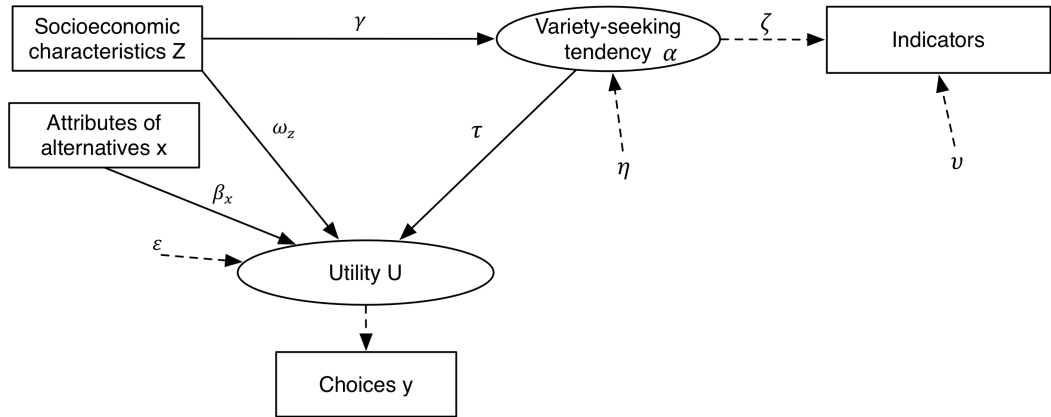


Fig. 2.4: Framework of the ICLV model

### 2.4.3.2 Choice model component

As shown in Eq.(2.7), the utility function is determined by both observable explanatory variables and the latent variable on variety-seeking. In our notation,  $\alpha_n$  denotes the latent variety-seeking tendency which varies over respondents, and  $\tau_i$  measures variety-seeking's impact on the utility of alternative  $i$ , with one  $\tau$  being fixed to 0 for identification.

$$U_{int} = V_{int} + \varepsilon_{int} = \mu_{\delta_i} + \sigma_{\delta_i} \xi_{in} + \tau_i \alpha_n + \beta' x_{int} + \omega'_i Z_n + \varepsilon_{int} \quad (2.7)$$

### 2.4.3.3 Latent variable model component

The structural equation in the latent variable model component explains the latent variable by some observable socioeconomic characteristics  $Z_n$ , which is

usually specified in a linear relationship with  $\gamma$  being the coefficient vector, such that:

$$\alpha_n = \gamma' Z_n + \eta_n, \quad (2.8)$$

where the stochastic error  $\eta_n$  follows a standard normal distribution across respondents, such that  $\eta_n \sim N(0, 1)$ .

In the measurement equations, responses to the attitudinal statements listed in Table 2.3 are treated as indicators to be explained by the latent variable of *variety-seeking tendency*, and each indicator requires a separate measurement equation. In recent years, a growing number of studies have recognized the ordinal characteristics of attitudinal indicators and have advocated the use of an ordered specification, as in Daly et al. (2012). For example, see Hess and Stathopoulos (2013) and Kamargianni et al. (2015). In this regard, the current paper differentiates itself from the work of Rieser-Schüssler and Axhausen (2012) by using an ordered specification instead of a continuous specification.

Following Daly et al. (2012), we use  $I_{nk}$  to denote the observed response to attitudinal statement  $k$  for respondent  $n$ . Using the coefficient  $\zeta_k$  to measure the impact of the individual-specific latent *variety-seeking tendency* on the response towards indicator  $k$ , the probability of the observed response  $I_{nk}$  can be written in an ordered logit form, such that:

$$P(I_{nk} = s | \alpha_n) = \frac{e^{(\mu_{k,s} - \zeta_k \alpha_n)}}{1 + e^{(\mu_{k,s} - \zeta_k \alpha_n)}} - \frac{e^{(\mu_{k,s-1} - \zeta_k \alpha_n)}}{1 + e^{(\mu_{k,s-1} - \zeta_k \alpha_n)}}, \quad (2.9)$$

where  $\mu_{k,s}$  are threshold parameters, and  $s \in (1, 2, 3, 4, 5, 6, 7)$  as a 7-point Likert scale was used.

For normalisation purpose, we set  $\mu_{k,0}$  to  $-\infty$  and  $\mu_{k,7}$  to  $+\infty$ . Therefore, in our case, only the intermediate six threshold values can be estimated for each indicator.

#### 2.4.3.4 Log-likelihood function

In the joint log-likelihood function, we need to maximise  $LL(y, I)$ , in which the unconditional probability  $P_n$  of observing choices  $y_n$  and attitudinal indicators  $I_n$  can be expressed as the integral of the multiplication of the conditional choice probability and the conditional indicator probability over all possible values of the latent variable, such that:

$$LL(y, I) = \sum_{n=1}^N \ln P_n \quad (2.10)$$



$$P_n = \int_{\delta_n} \int_{\alpha_n} \left( \prod_{t=1}^{T_n} P(y_{nt}|x_{nt}, Z_n, \alpha_n, \delta_n; \beta, \omega, \tau) \times \prod_{k=1}^{K_n} P(I_{nk}|\alpha_n; \mu_k, \zeta_k) \right) f(\alpha_n|Z_n; \gamma) f(\delta_n|\Omega_\delta) d(\alpha_n) d(\delta_n) \quad (2.11)$$

A second layer of integration is required to account for both unobserved heterogeneity and the latent variables. Again, the model is estimated using simulation to approximate the integrals.

## 2.5 Empirical analysis

### 2.5.1 Model specification

Three models were estimated, which examined the marginal utilities of various explanatory variables and to different extent accounted for taste heterogeneity and the impact of variety-seeking on mode choice in the context of HSR-air intermodality. We started with a MNL model without considering the impact of variety-seeking, nor the random taste heterogeneity, based on the utility function specified in Eq.(2.1). We then estimated a MMNL model by including random alternative-specific constants to accommodate random taste heterogeneity, following the utility function given in Eq.(2.3). We finally estimated an ICLV model as addressed in section 2.4.3, in which variety-seeking tendency was treated as a latent variable in the utility function rather than an exogenous explanatory variable and was also used in the measurement equations to explain the attitudinal indicators. The ICLV model accounted for the ordinal characteristics of attitudinal responses and treated both age and income as continuous variables in the structural equation to explain the latent variety-seeking tendency. It should be noted that in order to ensure fair comparison between the first two models and the ICLV model and to avoid overstating the benefit of applying an ICLV model, both the MNL and the MMNL model incorporated age and income in the utility function in a linear way (Vij and Walker, 2016). Additionally, in both the MMNL model and ICLV model, the integrated HSR-air alternative was chosen as the base alternative for normalisation as it had the lowest variance in the unidentified model (Walker et al., 2007), and 500 Halton draws were used per individual per random component in simulation-based estimation.

In each model, minor time, travel cost and connection time were treated as continuous variables, while other attributes were dummy coded and entered the utility functions as categorical variables. Travel cost was a generic variable in each model. Minor time of car-air/air-air was differentiated from that of separated/integrated HSR-air, with each being further split between business travels

and non-business travels. Delay protection was interacted with the response to “*Are you familiar with the transfer city Shanghai?*”, a self-reported question with three available options (i.e. not familiar at all, familiar and very familiar). The attribute of luggage integration was interacted with the number of check-in luggage of the respondent for current travel.

## 2.5.2 Estimation results

### 2.5.2.1 MNL and MMNL models

The estimation results of MNL and MMNL models are presented in Table 2.4. The alternative-specific constant (ASC) for car-air is always negative, indicating that, all else being equal, the overall preference for car-air is lower than that of integrated HSR-air (i.e. the base alternative). No significant ASC for air-air or separated HSR-air is discovered, suggesting no underlying preference over or below integrated HSR-air.

The estimates for various utility parameters show similar patterns in MNL and MMNL models and almost all of them have expected signs - respondents derive a positive utility from reductions in travel time (including minor time, connection time, transfer time) and travel cost and from improvements in additional service, i.e. delay protection, and luggage integration. The only less intuitive finding arises for the insignificant estimates for ticket integration, which is ambiguously perceived by respondents, a finding that could potentially be attributed to two reasons. Firstly, some respondents do not experience difficulties in purchasing/collecting tickets separately, thereby feeling no urge to pay for the integrated service; secondly, some respondents doubt whether integrated service could guarantee them the flexibility of choosing airlines on the major leg and do not want to rush into this new market when it is not fully developed.

Dividing the sensitivity of different minor time by the sensitivity of cost, we can obtain the value of time (VoT) for each group. The calculations of value of minor time are summarised in Table 2.5. It can be inferred that whether for business travellers or for non-business travellers, the VoT is much higher if the minor leg is made by car or air (i.e. car-air or air-air alternative) than by HSR (i.e. separated or integrated HSR-air alternative), reflecting the superior comfort experienced in high-speed trains. The VoT difference between car/air and HSR for business travellers might also be due to the fact that business travellers use more travel time for work than for other activities, and that compared to working during car travel or air travel, working during train journeys is more favourable (Hultkrantz, 2013). The VoT of business travellers is about twice that of non-

## 2.5. Empirical analysis

**Table 2.4:** Model estimation results (choice model component and structural equations)

	MNL			MMNL			ICLV		
individuals #	123			123			123		
observations #	984			984			984		
total parameters #	21			24			88		
$LL(0)$	-1364.114			-1364.114			whole model: -3442.394		
$LL(\text{final})$	-1136.04			-1035.19			SC component: -1034.743		
adj. $\rho^2$	0.1518			0.2235			whole model: 0.1688		
$AIC$	2314.08			2118.39			whole model: 5722.79		
$BIC$	2416.81			2235.79			whole model: 6153.26		
	est.	$t$ -rat.	$p$ -value	est.	$t$ -rat.	$p$ -value	est.	$t$ -rat.	$p$ -value
$\mu_{\delta_{car-air}}$	-2.140	-3.01	0.003	-2.959	-2.82	0.005	-3.335	-3.01	0.003
$\mu_{\delta_{air-air}}$	-0.012	-0.04	0.968	0.174	0.44	0.660	0.176	0.45	0.653
$\mu_{\delta_{separatedHSR-air}}$	-0.169	-0.53	0.596	-0.520	-1.24	0.215	-0.554	-1.30	0.194
$\sigma_{\delta_{car-air}}$	-	-	-	-2.264	-7.48	0.000	-2.254	-4.84	0.000
$\sigma_{\delta_{air-air}}$	-	-	-	-0.965	-6.23	0.000	-0.959	-6.35	0.000
$\sigma_{\delta_{separatedHSR-air}}$	-	-	-	1.438	8.12	0.000	1.347	9.08	0.000
$AGE_{separatedHSR-air}$	-0.427	-2.67	0.008	-0.454	-2.34	0.019	-0.566	-2.85	0.004
$INCOME_{car-air}$	0.241	1.77	0.077	0.282	1.41	0.159	0.311	1.60	0.110
$INCOME_{separatedHSR-air}$	0.126	1.39	0.165	0.124	1.03	0.303	0.186	1.46	0.145
$\beta_{MinorTime\_car/air\_Business}$	-0.013	-3.30	0.001	-0.018	-3.28	0.001	-0.017	-2.85	0.004
$\beta_{MinorTime\_car/air\_NonBusiness}$	-0.007	-2.56	0.011	-0.011	-2.97	0.003	-0.011	-3.06	0.002
$\beta_{MinorTime\_HSR\_Business}$	-0.009	-4.10	0.000	-0.011	-3.93	0.000	-0.010	-3.61	0.000
$\beta_{MinorTime\_HSR\_NonBusiness}$	-0.004	-2.39	0.017	-0.004	-2.18	0.029	-0.004	-2.30	0.022
$\beta_{ConnectionTime}$	-0.009	-8.66	0.000	-0.011	-8.70	0.000	-0.011	-8.65	0.000
$\beta_{TransferTime=45/90min}$	-0.633	-5.47	0.000	-0.801	-5.71	0.000	-0.801	-5.75	0.000
$\beta_{DelayProtection=lv1}$	0.281	2.24	0.025	0.338	2.30	0.022	0.340	2.31	0.021
$\beta_{DelayProtection=lv2\&unfamiliar}$	0.693	3.51	0.000	0.670	2.98	0.003	0.653	2.90	0.004
$\beta_{DelayProtection=lv2\&familiar}$	0.369	2.54	0.011	0.479	2.98	0.003	0.491	3.10	0.002
$\beta_{TicketIntegration=lv2}$	0.155	0.94	0.347	0.203	1.08	0.280	0.193	1.03	0.303
$\beta_{TicketIntegration=lv3}$	-0.135	-0.82	0.412	-0.026	-0.14	0.889	-0.039	-0.22	0.826
$\beta_{LuggageIntegration=lv12\&\leq 1luggage}$	0.362	2.04	0.042	0.388	1.98	0.048	0.413	2.13	0.033
$\beta_{LuggageIntegration=lv1\&> 1luggage}$	0.564	1.97	0.049	0.714	2.24	0.025	0.690	2.12	0.034
$\beta_{LuggageIntegration=lv2\&> 1luggage}$	0.923	3.74	0.000	0.920	3.14	0.002	0.894	3.02	0.003
$\beta_{TravelCost}$ (CNY)	-0.002	-6.11	0.000	-0.002	-6.07	0.000	-0.002	-6.13	0.000
$\tau_{car-air}$	-	-	-	-	-	-	-0.907	-4.28	0.000
$\tau_{air-air}$	-	-	-	-	-	-	-0.008	-0.06	0.952
$\tau_{separatedHSR-air}$	-	-	-	-	-	-	-0.310	-1.94	0.053
$\gamma_{Age}$	-	-	-	-	-	-	-0.300	-2.76	0.006
$\gamma_{Income}$	-	-	-	-	-	-	0.143	1.78	0.075

business travellers, suggesting that passengers would be more unwilling to spend longer time on the minor leg if they are travelling for business. Such findings of higher VoT for business travellers are consistent with other value-of-time studies. For example, [González-Savignat \(2004\)](#) discovered the value of travel time to be 55eur/h (37 eur/h) for business (leisure) travellers.

**Table 2.5:** Value of time calculations

	Value of Time (CNY/min)			
	MNL	MMNL	ICLV	Change (%)
MinorTime_car/air_Business	6.45	7.58	6.83	-9.91
MinorTime_car/air_NonBusiness	3.50	4.38	4.62	5.55
MinorTime_HSR_Business	4.35	4.46	4.10	-8.14
MinorTime_HSR_NonBusiness	1.85	1.71	1.77	3.57

VoT studies in China are quite limited, and official VoT statistics are not available ([Wu et al., 2014](#)). [Hultkrantz \(2013\)](#) indicated the upper margin of VoT of business travellers by rail on the Beijing-Shanghai corridor to be 2.07 CNY/min through calculating the break-even VoT that equalises the generalised cost of HSR and air; [Wang et al. \(2014\)](#) obtained a VoT estimate ranging from 0.33 to 1.4 CNY/min for different types of HSR travellers on the intra-provincial Ningbo-Taizhou-Wenzhou corridor through nested logit model on revealed-preference data; [Li and Sheng \(2016\)](#) estimated the VoT for en route travel (relating to both minor leg and major leg) in the context of HSR-air intermodality based on stated-preference data, showing a highest VoT of 2.17 CNY/min for direct air travel, followed by 1.84 CNY/min for integrated travel, and 1.47 CNY/min for direct HSR travel. In contrast, our inferred VoT estimates are much higher but still comparable. This can be largely attributed to that our sample composition is not representative of the general Chinese population. [Wu et al. \(2014\)](#) suggested that the unbalanced economic development and the large income gap in China would result in huge variation of VoT across regions and income groups, and their estimates, which were derived based on the average wage and social welfare payment, showed that the VoT for business travellers of the highest 20% income group in Shanghai can reach 2.36 CNY/min, followed by provinces in the Yangtze River Delta regions. Since the majority of our respondents came from these developed regions and were on international travels in particular, it is reasonable to achieve higher VoT estimates. In addition, what we suggest here is the value of time for accessing the airport which is usually higher than that for the en route component given the high penalty associated with missing a flight.

According to [Table 2.4](#), connection time is perceived to be no less important

than minor time except when the minor leg is made by car or air for business travellers, implying a great necessity of enhancing the coordination between air and HSR timetables. The significant negative estimate for transfer time suggests a strong dislike of moving between airports/ stations which are far away from each other. We did not find significant differences between the impact of 90min of transfer time and 45min of transfer time on mode choice, and this potentially means that passengers still feel averse to moving between two far-away airports/stations even if the transfer time could be reduced by half. Moreover, better delay protection is more attractive to passengers, and in particular, those who are unfamiliar with the transfer city Shanghai experience a higher positive utility from “free flight change” (level 2) than those who know Shanghai well, which indicates that people lacking travel information may perceive more uncertainty in travel and are willing to pay more for reducing risks. Finally, people with more check-in luggage have a stronger preference for luggage integration than people with less check-in luggage, while passengers with at most one piece of check-in luggage do not significantly differentiate between luggage integration with two security checks (level 1) or one security check (level 2). This is not the case for passengers with more than one check-in luggage, where one security check is significantly more appealing than two security checks.

Age and income are incorporated in the utility function as continuous explanatory variables. As the impact of age on car-air and air-air, and income on air-air was not significant even at the 60% confidence interval, we excluded them from the final models. The results show that respondents’ preference towards separated HSR-air decreases with age, which potentially results from the stronger inconvenience of separated service perceived by older passengers. The less significant estimates for income suggest that passengers with higher income might potentially derive more utility from the car-air or separated HSR-air alternatives compared to air-air or integrated HSR-air alternatives.

Moving from MNL to MMNL models, significant improvement in model fit is observed. The standard deviation of ASC for each alternative is significantly different from 0, where car-air presents the highest randomness compared to integrated HSR-air, followed by separated HSR-air and air-air. This confirms the existence of random heterogeneity across respondents in modal preferences.

### 2.5.2.2 ICLV model

In reporting the estimation results of the ICLV model, the overall log-likelihood and the log-likelihood for the choice model component are presented in the last two columns of Table 2.4. Compared to the MMNL model without the incorpora-

tion of variety-seeking, we cannot discover significant improvement in the choice log-likelihood of the ICLV model. This is consistent with the discussions in [Vij and Walker \(2016\)](#); since an ICLV model needs to explain both choice indicators and measurement indicators, the overall log-likelihood can never be better than that of the corresponding reduced form mixed logit model (i.e. MMNL). It can, however, of course give us different insights into behaviour.

We turn to the results for the measurement equations in the latent variable component in [Table 2.6](#) before looking at the estimates for the choice model component in [Table 2.4](#). All the attitudinal indicators, except for A4 and A9, are found to be affected by the latent variables as the corresponding  $\zeta$  are significant for those indicators. Thus, indicator A4 and A9 dropped out in the final models. The positive signs of  $\zeta_k (k = 1, 2, 3, 5, 6)$  and negative signs of  $\zeta_k (k = 7, 8, 10, 11)$  show that stronger latent variable  $\alpha$  would lead to an increase in the response to the attitudinal statements A1, A2, A3, A5 and A6, which means an increase in the extent that the respondent agrees with the statement, and meanwhile would result in a lower score on the attitudinal statements A7, A8, A10 and A11, which means a stronger disagreement with the statement. This means that  $\alpha$  stands for the “variety-seeking tendency”. In addition, the uneven gap between thresholds proves the necessity and superiority of adopting an ordered logit formation to account for the ordinal characteristics of attitudinal indicators in measurement equations. It should be noted that since no respondent provided a score of 1 for A1 and A5, and no respondent provided a score of 7 for A7 and A11, threshold coefficients  $\mu_1$  for A1 and A5 as well as  $\mu_6$  for A7 and A11 are not estimated. The relationships between latent variety-seeking tendency and socioeconomic characteristics is detected to some extent in the structural equations:  $\gamma_{Age}$  is estimated to be -0.300 ( $t$ -rat.=-2.76) and  $\gamma_{Income}$  to be 0.143 ( $t$ -rat.=1.78). This implies that younger people or people with higher income tend to have stronger variety-seeking tendencies.

Back to [Table 2.4](#), the signs for all the ASC and utility coefficients are identical to those obtained in the MNL and MMNL models and are not discussed here for brevity. As for the estimates for the marginal impact of the latent variables on utility, our results show that an increase of the latent variety-seeking tendency leads to a lower utility for car-air or separated HSR-air (given the negative sign for  $\tau_{car-air}$  and  $\tau_{separatedHSR-air}$ ), and that variety-seeking does not result in a difference in modal preference between air-air and integrated HSR-air. This implies that people who have weaker variety-seeking tendencies are more likely to choose car-air or separated HSR-air, and variety-seekers have a higher propensity to choose the air-air alternative or the new integrated HSR-air alternative.

## 2.5. Empirical analysis

It is also of interest to see what share of the random heterogeneity in the choice model can be attributed to the latent variables (see Table 2.7). This can be obtained by calculating the ratio of the variance of randomness induced by the latent variable and the variance of total randomness. For the heterogeneity in the car-air alternative, we see that 86.06% is pure random heterogeneity, while the remaining 13.94% is linked to the latent variety-seeking variable. For air-air, the share of the random variance is much higher, at 99.99%, leaving little explanatory power for the latent construct. For separated air-HSR, we see that 5.04% can be attributed to the latent variety-seeking tendency. Overall, these findings support the notion that variety-seeking plays a role in mode choice behaviour in our sample, albeit a small one.

Finally, if we look at the last column in Table 2.5 which summarises the changes of different value of minor time between the MMNL model and the ICLV model. It can be implied that the VoT for business travellers might be overestimated while the VoT for non-business travellers might be underestimated if the impact of latent variety-seeking tendency is not accounted for in a MMNL model.

**Table 2.6:** Estimation results of the measurement equations of the ICLV model

Indicator	$\zeta$		$\mu_1$		$\mu_2$		$\mu_3$		$\mu_4$		$\mu_5$		$\mu_6$	
	est.	<i>t</i> -rat.	est.	<i>t</i> -rat.	est.	<i>t</i> -rat.	est.	<i>t</i> -rat.	est.	<i>t</i> -rat.	est.	<i>t</i> -rat.	est.	<i>t</i> -rat.
A1	0.652	2.74	-	-	-2.922	-7.24	-2.164	-6.62	-1.131	-4.39	0.131	0.53	2.672	6.53
A2	0.539	2.30	-4.411	-5.90	-2.018	-6.26	-1.259	-4.76	-0.095	-0.40	0.515	2.17	3.412	6.11
A3	0.688	2.56	-3.633	-6.10	-2.001	-5.28	-1.205	-3.68	-0.566	-1.92	0.151	0.55	2.415	6.27
A5	0.870	3.37	-	-	-4.018	-6.85	-2.551	-7.00	-1.416	-4.65	-0.150	-0.55	2.183	5.95
A6	1.354	4.16	-6.301	-4.32	-2.548	-4.62	-1.529	-3.30	-0.649	-1.56	0.554	1.44	3.488	5.50
A7	-0.805	-2.99	-4.231	-6.19	-1.508	-4.91	-0.809	-2.89	0.254	0.87	1.387	4.07	-	-
A8	-1.726	-4.43	-5.264	-6.15	-1.067	-2.23	0.041	0.09	1.341	2.75	2.743	4.64	5.651	5.43
A10	-1.230	-3.65	-3.841	-6.26	-0.478	-1.32	0.654	1.83	1.574	4.05	3.059	6.21	6.005	5.56
A11	-1.794	-3.58	-6.151	-5.47	-0.603	-1.29	0.931	2.00	2.310	4.13	4.248	5.63	-	-

**Table 2.7:** Sources of random taste heterogeneity

alternative	parameter		Components of variance of $\delta$			Random taste heterogeneity %	
	$\sigma$	$\tau$	pure random	linked to the latent variable	combined	pure random	linked to the latent variable
car-air	-2.25	-0.91	5.08	0.82	5.90	86.06%	13.94%
air-air	-0.96	-0.01	0.92	0.00	0.92	99.99%	0.01%
separated HSR-air	1.35	-0.31	1.81	0.10	1.91	94.96%	5.04%



## 2.6 Discussions and conclusions

This paper focuses on mode choice behaviour in the recently-emerged intercity travel market of HSR-air intermodality in China. It looks in particular at how variety-seeking could influence the mode choice decisions in this new context. Our research is motivated by two distinct factors. Firstly, although a large body of research on variety-seeking has been accumulated in consumer marketing, limited knowledge of its effect is available in the transport realm, whilst various novel transport services have emerged in recent years, such as low-emission vehicles and shared vehicles. HSR-air intermodality is a key example of such a new service for the majority of Chinese people. Secondly, though many researchers have initiated discussion on the cooperation between air and HSR in the perspective of pricing strategy, traffic volume and welfare analysis, etc., limited econometric studies has been conducted to investigate the mode choice behaviour on an individual level in this context. Following previous Spanish research, we carry out a comparable study in China, which has the world's largest HSR network and enjoys a rapid and steady increase in international travel, implying a great potential for enhancing cooperative intermodality between the two systems of air and HSR.

An integrated choice and latent variable (ICLV) model is estimated in this paper to account for the impact of latent variety-seeking tendency in mode choice behaviour in the new context of HSR-air intermodality. Variety-seeking is used to explain both the attitudinal indicators in measurement equations and the choices made in the stated preference survey. The results of ICLV model show that variety seekers have a stronger propensity of choosing the new integrated HSR-air compared to car-air and separated HSR-air, while variety-seeking tendency does not have a significantly different impact between choosing air-air and integrated HSR-air. The most negative impact of variety-seeking on car travel compared to other public modes on minor leg confirms the findings in [Rieser-Schüssler and Axhausen \(2012\)](#), which also reflects the strong barrier of shifting drivers from behind their steering wheels to use public transport. In the structural equations, we used respondents' age and income to explain the latent variable which is interpreted as variety-seeking tendency. Results suggest that younger people and people with higher income present stronger inclinations to seek variety. Therefore, the HSR sector, airports and airline companies need to make a joint effort in identifying variety seekers and trying to keep those new customers by providing them with enjoyable travel experience. In particular, younger people and higher-income people should be treated as the target customers.

Turning to the impact of the level-of-service attributes, we observe higher values of minor time for business travellers compared to non-business travellers, and higher values of time if the minor leg is made by car or air than by HSR. This suggests that business passengers require shorter feeder journeys, and HSR travel is potentially perceived by either business travellers or non-business travellers as more comfortable than car travel or air travel. It is also shown that minor time is not more important than connection time except for the case for business travellers for the car-air or air-air alternative. This suggests the great necessity to improve the timetable coordination between flights and HSR trains as passengers dislike waiting at the departure airport for the major leg, which confirms the findings in previous studies (Li and Sheng, 2016; Román and Martín, 2014). Transferring between the Hongqiao Hub and Pudong International Airport is perceived as very inconvenient by intercity travellers, which indicates a sound prospect of attracting integrated HSR-air customers should the Pudong Hub be established. The higher the level of delay protection is, the more appealing it is to intercity passengers, with free flight change being the most attractive level; moreover, the free flight change in case of HSR delays resulting in failure to board the plane on the major leg is in particular more attractive to passengers who are not familiar with the transfer city Shanghai. Therefore, it is necessary for policy makers and transport operators to clarify the rights and responsibilities of different sectors, and to establish practical mechanisms to protect passengers' travel as well as to attract more potential customers. Better integrated luggage handling service is welcomed by passengers, especially those with more luggage. Therefore, it would attract more customers if the integrated luggage handling system is available. However, we also need to be aware that such types of configuration updates might be very costly, therefore cost-benefit analysis is further required before policy makers decide to implement luggage integration system. Finally, the impact of ticket integration is much less clear, potentially suggesting that this is a less important attribute to look at for passengers. We also acknowledge that the small sample size might potentially be partly responsible for the insignificant estimates of parameters related to ticket integration. It may also suggest that the different levels for ticket integration is not sufficiently wide in between in the original design and simplifying the levels of ticket integration may be beneficial. However, from the perspective of system management, the advancement in other service attributes, e.g. better timetable coordination between flights and HSR trains, stronger delay protection and higher level of luggage integration, cannot be achieved without the implementation of a well-rounded integrated ticketing system which ensures a high level of information-sharing among stake-holders of

the HSR system and air system. In this regard, ticket integration should still be considered as an important factor for improving the integrated HSR-air service. Moreover, integrated ticketing systems could reach wider customers only when it is capable of providing passengers with sufficient options on departure time and airline companies, otherwise passengers might feel a barrier to try the integrated HSR-air service. Hence, it is imperative to launch more empirical analysis in the new context to explore how different extent of ticket integration would influence decisions.

For comparison, a basic MNL model and a MMNL model are estimated along with the ICLV model. Random taste heterogeneity is accounted for through random ASC specification in both MMNL and ICLV models; and the significant estimates of the standard deviation of random ASC confirm the existence of random taste heterogeneity across respondents and across alternatives.

Admittedly, this research does not make use of revealed preference (RP) data to jointly estimate with SP data to correct the scale of the model. Although our questionnaire required respondents to report their five most recent intercity trips including origins, destinations, total travel time and modes adopted. However, in the end, this information was not used mainly because the data indicated an insufficient use of the new mode among the sampled respondents. Since HSR-air intermodality is a new mode, it is reasonable to experience difficulties in obtaining sufficient amount of RP data from those who have experienced the new mode.

In closing, we put forward some avenues for future research. Firstly, it is worth investigating the impact of respondents' actual travel experience on their behaviour in the stated choice scenarios. Secondly, although our results have identified that younger people seek more variety and are more inclined to try the integrated HSR-air service, we cannot be sure that they would not gradually become more resistant to change when they grow older, or whether the variety-seeking pattern of those young people would be kept unchanged. This issue would not be limited to our context of HSR-air intermodality, and in order to address it, it would be interesting to collect longitudinal data which enables researchers to understand how variety-seeking tendencies evolve over time and influence choice behaviour. Thirdly, as mentioned in the text, our study only focuses on the short-run impact of variety-seeking in a stated preference survey, which could be equivalently interpreted as novelty-seeking. It is therefore worthwhile to further investigate the impact of variety-seeking tendencies in altering among different choices. Fourthly, it would improve the study if both the two different choice scenarios - minor leg comes before/after major leg - were presented to

respondents, as this would enable the researchers to detect the difference between respondents' sensitivities of the various alternative-specific attributes in each direction of travel. Finally, it would be worth investigating the role of information when new modes come into play, and its relationship with variety-seeking, i.e. to explore whether stronger information-seeking is related to stronger variety-seeking and higher probabilities to adopt the new mode. This research might help policy makers to more effectively reach target customers, as more exposure to the knowledge of the new mode may increase the probability to try the new mode.

## **Acknowledgment**

We are grateful for the approval of gate clearance from Shanghai Airport Corporation which enabled us to collect data from actual travellers. Fangqing Song acknowledges the support of the China Scholarship Council scholarship 201506260171 while Stephane Hess was supported by the European Research Council through the consolidator grant 615596-DECISIONS.

## References

- Adamowicz, W.L., 1994. Habit formation and variety seeking in a discrete choice model of recreation demand. *Journal of Agricultural and Resource Economics* , 19–31.
- Albalade, D., Bel, G., Fageda, X., 2015. Competition and cooperation between high-speed rail and air transportation services in europe. *Journal of transport geography* 42, 166–174.
- Ashok, K., Dillon, W.R., Yuan, S., 2002. Extending discrete choice models to incorporate attitudinal and other latent variables. *Journal of marketing research* 39, 31–46.
- Baumgartner, H., Steenkamp, J.B.E., 1996. Exploratory consumer buying behavior: Conceptualization and measurement. *International journal of Research in marketing* 13, 121–137.
- Ben-Akiva, M., Walker, J., Bernardino, A.T., Gopinath, D.A., Morikawa, T., Polydoropoulou, A., 2002. Integration of choice and latent variable models. *Perpetual motion: Travel behaviour research opportunities and application challenges* , 431–470.
- Bennett, E.M., Kemler, D., Levin, B.T., 1957. Emotional associations with air and rail transportation. *The Journal of Psychology* 43, 65–75.
- Blainey, S., Hickford, A., Preston, J., 2012. Barriers to passenger rail use: a review of the evidence. *Transport Reviews* 32, 675–696.
- Borgers, A., Van Der Heijden, R., Timmermans, H., 1989. A variety seeking model of spatial choice-behaviour. *Environment and Planning A* 21, 1037–1048.
- Brida, J.G., Martín, J.C., Román, C., Scuderi, R., 2017. Air and hst multimodal products. a segmentation analysis for policy makers. *Networks and Spatial Economics* , 1–24.
- Chiambaretto, P., Decker, C., 2012. Air–rail intermodal agreements: Balancing the competition and environmental effects. *Journal of Air Transport Management* 23, 36–40.
- Costa, J.D., 2012. Factors of air-rail passenger intermodality.

## References

- Daly, A., Hess, S., Patruni, B., Potoglou, D., Rohr, C., 2012. Using ordered attitudinal indicators in a latent variable choice model: a study of the impact of security on rail travel behaviour. *Transportation* 39, 267–297.
- Dobruszkes, F., Givoni, M., 2013. Competition, integration, substitution: Myths and realities concerning the relationship between high-speed rail and air transport in europe, in: *sustainable aviation futures*. Emerald Group Publishing Limited, pp. 175–197.
- European Commission, D.G.f.M., Transport, 2011. White Paper on Transport: Roadmap to a Single European Transport Area: Towards a Competitive and Resource-efficient Transport System. Publications Office of the European Union.
- European Commission, D.G.f.M., 2010. High-speed Europe: A Sustainable Link Between Citizens. Publications Office of European Union.
- European Commission’s Directorate-General for Mobility and Transport, 2010. LINK Project: Intermodal Passenger Transport in Europe (the European forum on intermodal passenger travel). [http://www.rupprecht-consult.eu/uploads/tx\\_rupprecht/LINK\\_Guidance\\_Brochure.pdf](http://www.rupprecht-consult.eu/uploads/tx_rupprecht/LINK_Guidance_Brochure.pdf). Accessed: 2018-01-23.
- Givon, M., 1984. Variety seeking through brand switching. *Marketing Science* 3, 1–22.
- Givoni, M., Banister, D., 2006. Airline and railway integration. *Transport policy* 13, 386–397.
- Givoni, M., Chen, X., 2017. Airline and railway disintegration in china: the case of shanghai hongqiao integrated transport hub. *Transportation Letters* , 1–13.
- González, R.M., Marrero, Á.S., Cherchi, E., 2017. Testing for inertia effect when a new tram is implemented. *Transportation Research Part A: Policy and Practice* 98, 150–159.
- González-Savignat, M., 2004. Competition in air transport. *Journal of Transport Economics and Policy (JTEP)* 38, 77–107.
- Greene, W.H., Hensher, D.A., 2013. Revealing additional dimensions of preference heterogeneity in a latent class mixed multinomial logit model. *Applied Economics* 45, 1897–1902.

- Ha, J., Jang, S.S., 2013. Variety seeking in restaurant choice and its drivers. *International Journal of Hospitality Management* 32, 155–168.
- Hess, S., Stathopoulos, A., 2013. Linking response quality to survey engagement: a combined random scale and latent variable approach. *Journal of choice modelling* 7, 1–12.
- Hoyle, R.H., Stephenson, M.T., Palmgreen, P., Lorch, E.P., Donohew, R.L., 2002. Reliability and validity of a brief measure of sensation seeking. *Personality and individual differences* 32, 401–414.
- Hultkrantz, L., 2013. A note on high-speed rail investments and travelers' value of time. *Journal of Rail Transport Planning & Management* 3, 14–21.
- International Air Transport Association, 2003. Air/ Rail Intermodality Study. [http://www.pedz.uni-mannheim.de/daten/edz-os/gdv/03/2003\\_air\\_rail.pdf](http://www.pedz.uni-mannheim.de/daten/edz-os/gdv/03/2003_air_rail.pdf). Accessed: 2018-01-23.
- Jensen, A.F., Cherchi, E., Mabit, S.L., 2013. On the stability of preferences and attitudes before and after experiencing an electric vehicle. *Transportation Research Part D: Transport and Environment* 25, 24–32.
- Jiang, C., D'Alfonso, T., Wan, Y., 2017. Air-rail cooperation: Partnership level, market structure and welfare implications. *Transportation Research Part B: Methodological* .
- Jiang, C., Zhang, A., 2014. Effects of high-speed rail and airline cooperation under hub airport capacity constraint. *Transportation Research Part B: Methodological* 60, 33–49.
- Kamargianni, M., Dubey, S., Polydoropoulou, A., Bhat, C., 2015. Investigating the subjective and objective factors influencing teenagers' school travel mode choice—an integrated choice and latent variable model. *Transportation Research Part A: Policy and Practice* 78, 473–488.
- Kim, J., Rasouli, S., Timmermans, H., 2014. Hybrid choice models: principles and recent progress incorporating social influence and nonlinear utility functions. *Procedia Environmental Sciences* 22, 20–34.
- Kline, P., 2015. *A handbook of test construction (psychology revivals): introduction to psychometric design*. Routledge.
- Legohérel, P., Hsu, C.H., Daucé, B., 2015. Variety-seeking: Using the chaid segmentation approach in analyzing the international traveler market. *Tourism Management* 46, 359–366.

## References

- Li, Z.C., Sheng, D., 2016. Forecasting passenger travel demand for air and high-speed rail integration service: A case study of beijing-guangzhou corridor, china. *Transportation Research Part A: Policy and Practice* 94, 397–410.
- Maffii, S., Sitran, A., Brambilla, M., Martino, A., Mandel, B., Schnell, O., 2012. Integrated ticketing on long-distance passenger transport services. Brussels: European Parlements Committee on Transport and Tourism .
- Martín, J.C., Román, C., 2013. Wtp for the integration between the hsr and air transport at madrid barajas airport1., in: *International Choice Modelling Conference*, University of Sydney, Australia.
- McAlister, L., Pessemier, E., 1982. Variety seeking behavior: An interdisciplinary review. *Journal of Consumer research* 9, 311–322.
- McFadden, D., et al., 1973. Conditional logit analysis of qualitative choice behavior .
- Metrics, C., 2012. Ngene 1.1. 1 user manual & reference guide. Sydney, Australia: ChoiceMetrics .
- Ministry of Transport of the People’s Republic of China, 2017. Statistical bulletin of China’s transportation development in 2016. [http://www.zizhan.mot.gov.cn/zfxxgk/bnssj/zhghs/201704/t20170417\\_2191106.html](http://www.zizhan.mot.gov.cn/zfxxgk/bnssj/zhghs/201704/t20170417_2191106.html). Accessed: 2018-01-23.
- Oreg, S., 2003. Resistance to change: developing an individual differences measure. *Journal of applied psychology* 88, 680.
- Raju, P.S., 1980. Optimum stimulation level: Its relationship to personality, demographics, and exploratory behavior. *Journal of consumer research* 7, 272–282.
- Rieser-Schüssler, N., Axhausen, K., 2012. Investigating the influence of environmentalism and variety seeking on mode choice. *Transportation Research Record: Journal of the Transportation Research Board* , 31–41.
- Román, C., Martín, J.C., 2014. Integration of hsr and air transport: Understanding passengers’ preferences. *Transportation Research Part E: Logistics and Transportation Review* 71, 129–141.
- Rose, J.M., Bliemer, M.C., 2007. Stated preference experimental design strategies, in: *Handbook of Transport Modelling: 2nd Edition*. Emerald Group Publishing Limited, pp. 151–180.



- Schüssler, N., Axhausen, K.W., 2011. Psychometric scales for risk propensity, environmentalism and and variety seeking. [Working paper Transport and Spatial Planning] 725.
- Thøgersen, J., 2006. Understanding repetitive travel mode choices in a stable context: A panel study approach. *Transportation Research Part A: Policy and Practice* 40, 621–638.
- Van Trijp, H.C., Hoyer, W.D., Inman, J.J., 1996. Why switch? product category: level explanations for true variety-seeking behavior. *Journal of Marketing Research* , 281–292.
- Van Trijp, H.C., Steenkamp, J.B.E., 1992. Consumers' variety seeking tendency with respect to foods: measurement and managerial implications. *European Review of Agricultural Economics* 19, 181–195.
- Vespermann, J., Wald, A., 2011. Intermodal integration in air transportation: status quo, motives and future developments. *Journal of Transport Geography* 19, 1187–1197.
- Vij, A., Walker, J.L., 2016. How, when and why integrated choice and latent variable models are latently useful. *Transportation Research Part B: Methodological* 90, 192–217.
- Walker, J.L., Ben-Akiva, M., Bolduc, D., 2007. Identification of parameters in normal error component logit-mixture (neclm) models. *Journal of Applied Econometrics* 22, 1095–1125.
- Wang, Y., Li, L., Wang, L., Moore, A., Staley, S., Li, Z., 2014. Modeling traveler mode choice behavior of a new high-speed rail corridor in china. *Transportation Planning and Technology* 37, 466–483.
- Weber, E.U., Blais, A.R., Betz, N.E., 2002. A domain-specific risk-attitude scale: Measuring risk perceptions and risk behaviors. *Journal of behavioral decision making* 15, 263–290.
- Wu, J., Nash, C., Wang, D., 2014. Is high speed rail an appropriate solution to china's rail capacity problems? *Journal of Transport Geography* 40, 100–111.
- Xia, W., Zhang, A., 2016. High-speed rail and air transport competition and cooperation: A vertical differentiation approach. *Transportation Research Part B: Methodological* 94, 456–481.

## References

Zanin, M., Herranz, R., Ladousse, S., 2012. Environmental benefits of air-rail intermodality: The example of madrid barajas. *Transportation Research Part E: Logistics and Transportation Review* 48, 1056–1063.

## Chapter 3

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

Fangqing Song<sup>1</sup>, Stephane Hess<sup>1</sup> & Thijs Dekker<sup>1</sup>

## 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 which exhibits intra-individual preference heterogeneity than alternation avoiders. This paper, therefore, provides empirical evidence about market shares when the new air taxi service enters the market*

---

<sup>1</sup>Institute for Transport Studies and Choice Modelling Centre, University of Leeds (UK)

*and helps to identify target customers.*

**Key words:** shared mobility, intra-individual preference heterogeneity, latent variable latent class model, variety-seeking, vertical take-off and landing

## 3.1 Introduction

### 3.1.1 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 sharing 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. [Bardhi and Eckhardt, 2012](#); [DeMaio, 2009](#); [Shaheen et al., 2010](#)). 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 before 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 have been found 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 the reduction of traffic congestion and green-house emission 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 in more trips overall ([Dong et al., 2018](#); [Hensher, 2018](#); [Jin et al., 2018](#)). Some passengers may be induced to make additional trips

### 3.1. Introduction

which would otherwise not be made if those convenient ride-sourcing services are unavailable. Also, ride-sourcing drivers need to make extra trips to serve passengers whilst they do not need to reach the destinations by themselves if such trip requests are not made and taken. Meanwhile, car emissions would be affected by traffic conditions. Thus, it is possible that the traffic congestion will be negatively affected and that the total emissions will further increase as a consequence of thriving ride-sourcing services. 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). The UK national statistics (Office for National Statistics, 2019) also suggest that from 1990 to 2017, while the total greenhouse gas emissions dropped by 32%, those from road transport have increased by 6%, which is however much slower than the growth in road traffic. In this context, much more effort is required to achieve traffic amelioration and emission reduction. Besides, it is imperative to explore people’s willingness to switch from existing less green modes (e.g. conventional personal vehicles) to the new travel modes to achieve sustainability globally.

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 NASA 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 (Goyal, 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<sup>2</sup>. Also, the deployment of VTOL would not take up much valuable urban

---

<sup>2</sup>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 the large-scale commercialised operation of UAM, such as safety, noise, emission and vehicle performance (Holden and Goel, 2016). Ultimately, drones will be adopted to transport

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.<sup>3</sup>

### 3.1.2 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. [Hess et al., 2018](#); [Park and Ha, 2006](#); [Román et al., 2007](#)). Regarding urban travel, air travel 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 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. [Baik et al. 2008](#); [Joshi et al. 2014](#); [Pu et al. 2014](#)). 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, rather than the novel UAM services. More recently, [Fu et al. \(2018\)](#) used stated choice data to examine mode choice behaviour amongst private car, public transit, autonomous vehicle and autonomous VTOL air taxi via MNL models. However, the model specification could have been improved to better account for preference heterogeneity across respondents. In particular, passengers, which are expected to create zero emissions.

---

<sup>3</sup>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 the U.S. which has caused much criticism ([Koopman and Dourado, 2017](#)).

### 3.1. Introduction

although the author had collected information related to respondents' attitudes towards adopting new autonomous transportation modes, this information was not accommodated in the model. 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 change 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 of variety-seeking have been widely addressed in consumer and psychology research (e.g. (Borgers et al., 1989; Chintagunta, 1998; Givon, 1984)), they are rarely accommodated in discrete choice analyses using stated choice data in the transport realm. Notwithstanding this, capturing the impact of variety-seeking tendencies on mode choice behaviour in the new context would be advantageous to more behaviourally realistic interpretation, better identification of target customers and more efficient market segmentation.<sup>4</sup>

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. Can variety-seeking reflect itself through the novelty-seeking aspect and whether variety seekers have a higher probability to show higher inclination

---

<sup>4</sup>Please refer to section 1.2.2.1 for detailed discussions on variety-seeking.

to adopt the new service of interest?

2. Can variety-seeking reflect itself through the alternation aspect and whether variety seeker have higher tendencies to switch their choices more often over time?
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 two-layer latent variable latent class (2L-LV-LC) model is explained step by step, followed by a discussion of the estimation results. Conclusions are presented in the last section.

## 3.2 Survey and data

The University of Leeds, UK was provided with anonymized data by Uber Technologies, Inc. ("Uber"). Neither the University of Leeds nor the authors received funding or financial support from Uber, and the views, opinions, and conclusions expressed in this article are those of the authors and do not constitute any representation of Uber.

### 3.2.1 UberAIR service context

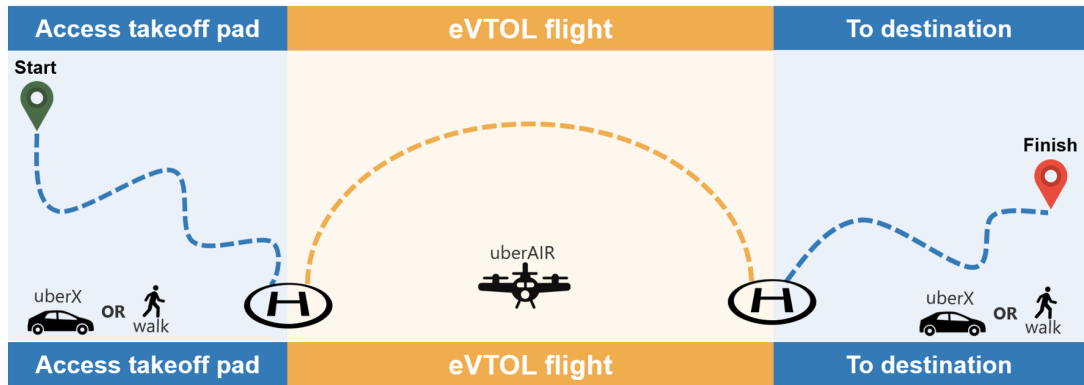
This paper makes use of stated choice (SC) data provided by Uber on mode choice amongst different alternatives including its upcoming on-demand electric VTOL air taxi service, i.e. UberAIR. It is expected to cut existing door-to-door travel times by an estimated 30% to 60% and create zero emissions and 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. 3.1 illustrates the UberAIR service.

### 3.2.2 Questionnaire and respondent sampling

Since the commercialised operation of UberAIR has not yet been realised, we cannot use revealed preference (RP) data to analyse people's preferences and



### 3.2. Survey and data



**Fig. 3.1:** Illustration of UberAIR service.

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 target 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-sourcing);
- 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 modelling work only makes use of the responses from qualified participants who completed the whole questionnaire. Although disqualified respondents were presented with attitudinal statements, this information is not used for model estimation in the current study.

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 3.1 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 the sample. In contrast, much fewer people used rental vehicle/car-share service, taxicab, other ride-sourcing service or UberBLACK/UberSELECT for their reference trips.

**Table 3.1:** Reference trips of sampled respondents

	Frequency	Percentage (out of 2607 respondents)
<b>Trip purpose</b>	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%
	<b>Trip mode</b>	Personal/Household vehicle
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%

Before proceeding to further analysis, we stress that the individual-specific reference mode was always shown as the first alternative in the SC survey; mean-

while, 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, 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 traveling 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.

### 3.2.3 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 a delay due to traffic congestion on the trip, how many people were in the vehicle on the trip, etc.

Table 3.2 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 3.3 describes the distribution of various socio-demographic characteristics. Respondents from the Dallas area and Los Angeles area are relatively

**Table 3.2:** 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

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. Census 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.

### 3.2.4 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. 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 included additional UberAIR options. Fig. 3.2 gives an example of a stated choice task where UberPOOL was

### 3.2. Survey and data

**Table 3.3:** 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%
Household vehicle	70 or older	97	4.0%
	None	151	6.2%
	1 vehicle	809	33.4%
	2 vehicles	962	39.8%
	3 vehicles	331	13.7%
	4 vehicles	114	4.7%
Household annual income	5 or more vehicles	52	2.1%
	<\$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%	

Chapter 3. Fancy sharing an air taxi? Uncovering the impact of variety seeking on the demand for new shared mobility services

identified as the reference mode.

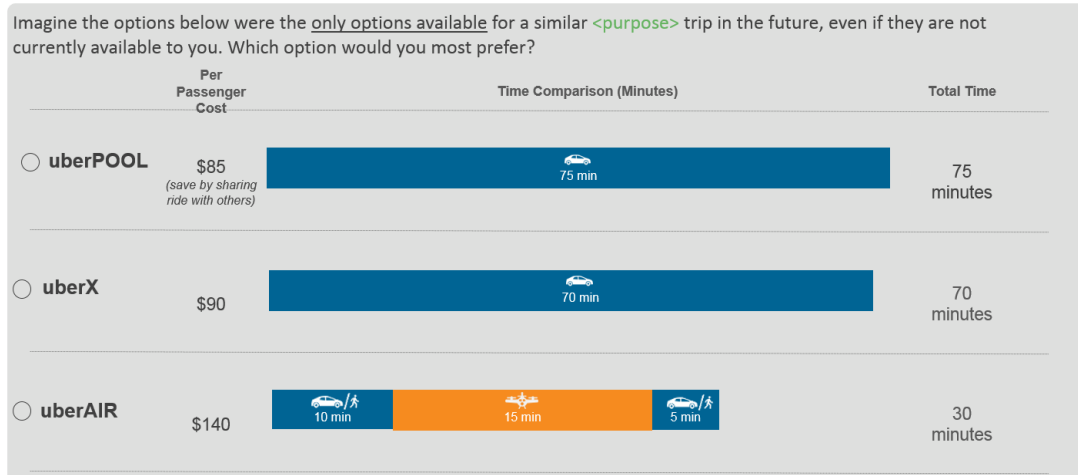


Fig. 3.2: Example of SC tasks.

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 except 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. Table 3.4 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 3.2.

Table 3.4: Summary of stated choice tasks

	Alternatives				
	private vehicle	transit	UberX	UberPOOL	UberAIR
<b>Attributes (median, mean)</b>					
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)

### 3.2.5 Attitudinal statements

In order to capture the influence of underlying psychometric constructs on choice behaviour, attitudinal statements were used to measure these unobserved factors. Before the factor analysis, we first excluded those statements from Table 3.5

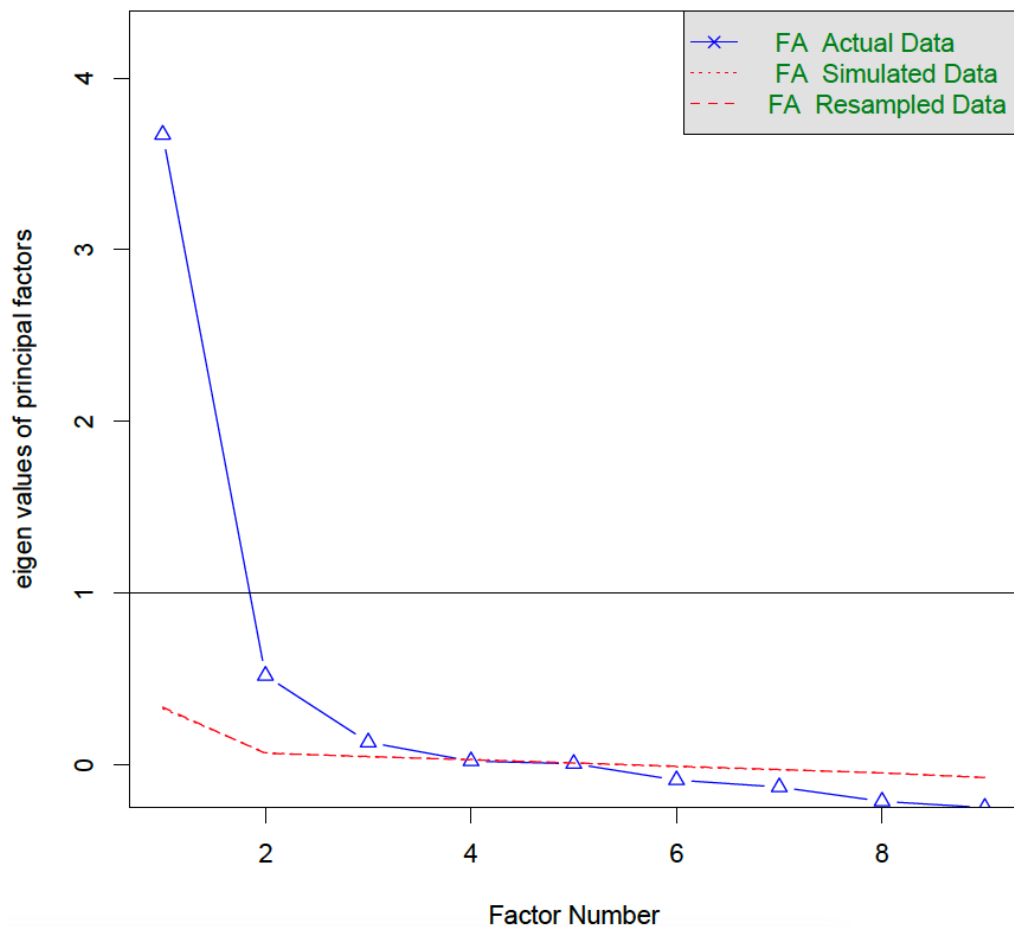
### 3.2. Survey and data

which were irrelevant from variety-seeking or were predicting some underlying constructs on their own. Then statements #4, #9 and #12 were not used for factor analysis as they were considered to be closely related to brand loyalty and lexicographic decision and environmental-friendliness in respective, which were distant from the other statements. The remaining statements were used in exploratory factor analysis and the scree plot shown in Fig. 3.3 suggested 2 to 4 factors could be suitable. We loaded the remaining 9 statements on 3 factors with a cut-off point of 0.5, and seven statements were identified, explaining 53% of the variance of the sample. That is, #8 and #10 for “variety-seeking”, #1 and #6 for “comfort of flying”, and #2, #7 and #11 for “dissatisfaction for status-quo”. Although statement #5 was related to variety-seeking, its loading was below the cut-off point and therefore was excluded.

**Table 3.5:** 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	<b>I am one of the first to adopt new technology</b>	<b>Variety-seeking</b>
9	I usually take the cheapest mode of transportation available to me	(not loaded on any factors)
10	<b>I'm excited for eVTOL travel to become available in my area</b>	<b>Variety-seeking</b>
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 3.5. 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 3.6 shows the average value for each index that reflects 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 a higher frequency of choosing the new UberAIR option and lower frequency of choosing the reference mode in the SC survey.



**Fig. 3.3:** Parallel analysis scree plots for the factor analysis.

**Table 3.6:** Relation between the response of attitudinal statements and mode choice experience/ stated choices

Score	reflection of alternation		reflection of novelty-seeking	
	Ride-sourcing companies used in real life (mean in group)	Different SC alternatives 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



### 3.3 Methodology

This section discusses the methodology for examining people’s preferences towards different level-of-service attributes and exploring the role of variety-seeking tendencies in mode choice behaviour in the new context when the innovative air taxi is introduced. As mentioned in section 3.1.2, variety-seeking can be reflected/driven by novelty-seeking and (or) alternation. Thus, we aim to distinguish and detect both aspects in our study. Specifically, the novelty-seeking aspect is accommodated based on the presumption that stronger novelty-seeking is linked to higher propensity to adopt the upcoming air taxi mode, i.e. UberAIR in our case. As such, part of preference heterogeneity across individuals can be explained. Nevertheless, the alternation aspect of variety-seeking is usually accommodated in longitudinal RP data that contains multiple choice observations over time for each respondent. Given that we only have SC data available, we adopt a different strategy to account for the alternation effect based on the assumption that stronger alternation would relate to higher tendency to exhibit unstable preferences over choice tasks of a SC survey. To put it in another way, we are going to associate the alternation aspect with preference heterogeneity over choices within a given individual, i.e. intra-individual preference heterogeneity.

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 (Becker et al., 2018; Hess and Giergiczny, 2015; Hess and Rose, 2009; Hess and Train, 2011). 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 to explain class allocation probabilities. A new two-layer Latent Variable Latent Class (2L-LV-LC) model is proposed, where respondents can be probabilistically classified into “novelty-seekers” class and “novelty-avoiders” class and continue to be segmented into “alternation-seekers”

class and “alternation-avoiders” class. This two-step segmentation allows us to capture preference variations across individuals. Meanwhile, the alternation effect is controlled only within the “alternation-seekers” class by implementing probabilistic allocation on discrete distributions over choice tasks, i.e. allowing for intra-individual preference heterogeneity. 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.

### 3.3.1 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 utility  $U_{int}$  from alternative  $i$  in choice task  $t$ , which is consisted of a deterministic portion  $V_{int}$  and unobserved and random disturbance  $\varepsilon_{int}$ . The utility function is written as:

$$U_{int} = V_{int} + \varepsilon_{int} = \delta_i + \beta' x_{int} + \varepsilon_{int}, \quad (3.1)$$

where  $V_{int}$  typically follows a linear-in-parameter specification with an alternative-specific constant (ASC)  $\delta_i$ .  $x_{int}$  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  $\beta$  explains the sensitivities and is treated as homogeneous across respondents and across choice tasks. The random error term  $\varepsilon_{int}$  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  $U_{int} \geq U_{jnt}, \forall j \in (1, \dots, J)$ . The probability of choosing alternative  $i$  out of the  $J$  alternative by respondent  $n$  in task  $t$  is thus given by:

$$P(y_{nt} = i) = \frac{e^{V_{int}}}{\sum_{j=1}^J e^{V_{jnt}}}. \quad (3.2)$$

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:

$$LL(y) = \sum_{n=1}^N \ln \left( \prod_{t=1}^T P(y_{nt} | \delta, \beta) \right). \quad (3.3)$$

### 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 (Gupta and Chintagunta, 1994; Kamakura and Russell, 1989). 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 3.3.1. 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  $\delta_s$  and sensitivities vector  $\beta_s$ ) 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. (3.1) can be replaced by:

$$U_{int,s} = V_{int,s} + \varepsilon_{int,s} = \delta_{i,s} + \beta'_s x_{int} + \varepsilon_{int,s}, \quad s \in (1, 2). \quad (3.4)$$

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  $\pi_s$  of a given respondent  $n$  falling into class  $s$  can be computed by:

$$\begin{aligned} \pi_1 &= \frac{e^{\gamma_1}}{e^{\gamma_1} + 1}, \\ \pi_2 &= 1 - \pi_1 \end{aligned} \quad (3.5)$$

such that  $\sum_{s=1}^S \pi_s = 1$  and  $0 \leq \pi_s \leq 1$ , where  $\gamma_1$  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:

$$P(y_n) = \sum_{s=1}^S \pi_s \left( \prod_{t=1}^T P(y_{nt} \mid \delta_s, \beta_s) \right). \quad (3.6)$$

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

### 3.3.3 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 the discrete mixture at both inter-individual and intra-individual layers, which can substantially reduce the computational burden. Besides, the alternation effect is controlled at the intra-individual layer to manifest preference variation across choice tasks. Fig. 3.4 illustrates how the sample is probabilistically classified at the inter-individual layer and how the alternation effect is controlled at the intra-individual layer. The model with latent variety-seeking is later discussed in section 3.3.4.

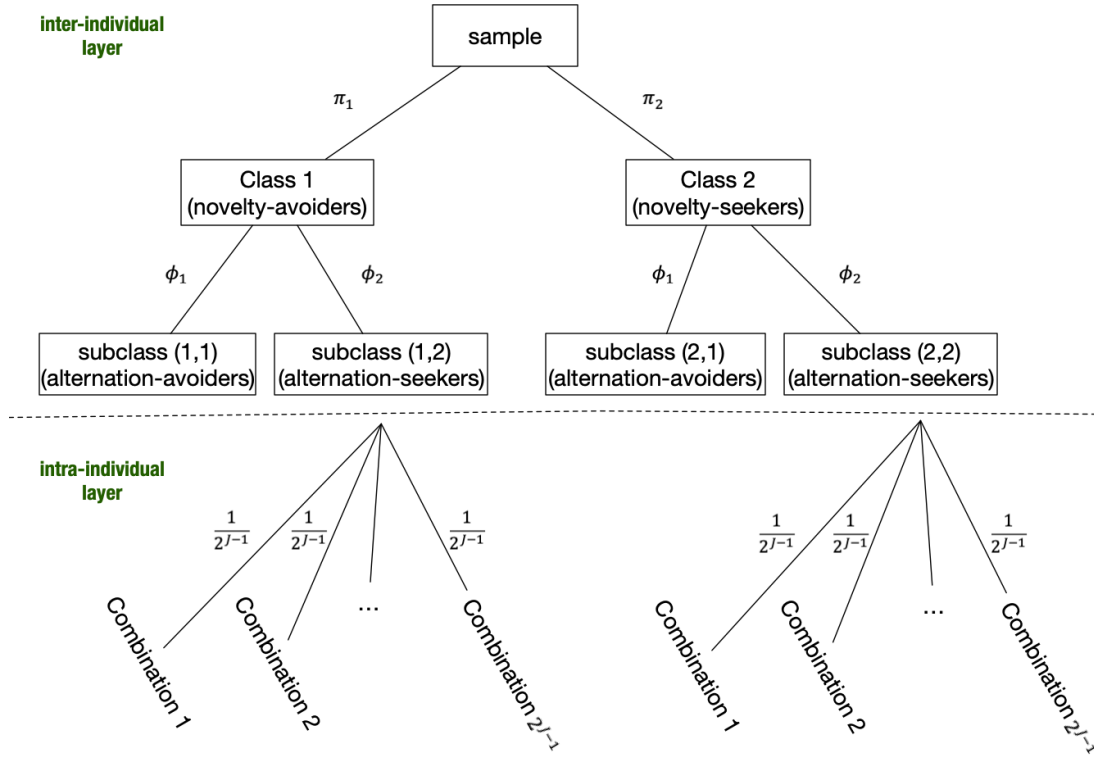


Fig. 3.4: Structure of the 2L-LC model.

### 3.3.3.1 Inter-individual layer

At the inter-individual layer, respondents are first of all probabilistically segmented into  $S$  classes, each class carrying different preference parameters. Obviously, this is the same as the basic LC model in section 3.3.2. That is, a given respondent has a probability of  $\pi_s$  to belong to class  $s$  with ASC  $\delta_s$  and sensitivities  $\beta_s$  which are specific to class  $s$ . In our case,  $S = 2$  as we expect to detect one class of “novelty-avoiders” and one class of “novelty-seekers”.

We continue to segment class  $s$  based on the assumption that while some individuals have consistent preference across choice tasks (i.e. alternation-avoiders), others experience preference variation in the course of completing choice tasks (i.e. alternation-seekers). That is, for each class  $s$ , it is further segmented into a “alternation-avoiders” subclass with a probability of  $\phi_1$ , and a “alternation-

### 3.3. Methodology

seekers” subclass with a probability of  $\phi_2$ . Herein, we use  $(s, q)$  to denote a subclass, with  $q = 1$  standing for a “alternation-avoiders” subclass, and  $q = 2$  for a “alternation-seekers” subclass. As shown in the upper part of Fig. 3.4, we eventually obtain four subclasses of respondents, among which (1, 1) and (2, 1) are “alternation-avoiders” subclasses with stable preference across tasks, whereas (1, 2) and (2, 2) are “alternation-seekers” subclasses exhibiting heterogeneous preference over tasks.

Therefore, while keeping the class allocation model at upper part the same as in Eq. (3.5), we further adopt another binary logit model within each class to determine the class allocation probability at the lower part such that:

$$\begin{aligned}\phi_1 &= \frac{e^{\lambda_1}}{e^{\lambda_1} + 1}, \\ \phi_2 &= 1 - \phi_1\end{aligned}\tag{3.7}$$

where  $\lambda_1$  is the constant specific to “alternation-avoiders” subclasses in the class allocation function. Herein,  $\lambda_1$  (and so is  $\phi_1$ ) is kept generic in any class  $s$  to facilitate the identification of the 2L-LC model and the more complex 2L-LV-LC model. We acknowledge that this restriction may overlook the differences regarding the alternation probabilities between novelty-seekers class and novelty-avoiders class. We will leave this for future research to improve the examination of the role of novelty-seeking aspect and alternation aspect.

As to the “alternation-avoiders” subclasses (i.e.  $q = 1$ ), they are characterised with the baseline preference parameters  $\delta_s$  and  $\beta_s$  at each choice. Thus, the utility function for alternative  $i$  given the class membership  $(s, 1)$  is written as:

$$U_{int,(s,1)} = \delta_{i,(s,1)} + \beta'_{(s,1)}x_{int} + \varepsilon_{int,(s,1)} = \delta_{i,s} + \beta'_s x_{int} + \varepsilon_{int,(s,1)}, \quad s \in (1, 2), \tag{3.8}$$

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

$$P(y_{nt} | \delta_{(s,1)}, \beta_{(s,1)}) = P(y_{nt} | \delta_s, \beta_s). \tag{3.9}$$

As to the “alternation-seekers” subclasses (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 alternation-seeking subclasses in section 3.3.3.2.

It needs to be noted that it is technically possible to reverse the order of this two-step segmentation across individuals. That is, the sample could be first probabilistically segmented into alternation-avoiders class and alternation-seekers class, and each class be further segmented into a novelty-avoiders subclass and novelty-seekers class. This is because the two-step segmentation consists of two independent logit models so the class membership statements are independent and can be reversed.

### 3.3.3.2 Intra-individual layer

As stated earlier, we associate alternation effect with the tendency to exhibit intra-individual preference heterogeneity. Given the allocation to a “alternation-seekers” subclass (i.e.  $q = 2$ ), the alternation effect is controlled by allowing for preference variations in parameters across choice tasks. Contrary to this, preferences are kept stable across choice tasks if allocated to a “alternation-avoiders” subclass. Specifically, the intra-individual preference heterogeneity is only accommodated for the “alternation-seekers” subclasses, by letting the ASC parameters  $\delta_{(s,2)}$  shift around the baseline values by  $\Delta$  at the observation level. The marginal utilities  $\beta_{(s,2)}$  are fixed to the baseline values of  $\beta_s$  over tasks, i.e. no intra-individual heterogeneity in the marginal utility parameters.

In order to manifest the variation of ASCs at the choice task level, we replace the continuous distributions across choices which are used in the MMNL model with discrete mixtures at the intra-individual layer. More precisely, we assume that each  $\delta_{i,s}$  has an equal probability to either have an alternative-specific shift term  $\Delta_i$  added or deducted, where  $\Delta_i$  is kept generic in any class  $s$ . Thus, we specify:

$$\delta_{i,(s,2)} = \delta_{i,(s,2),m_i} = \delta_{i,s} + \Delta_i(m_i == 1) - \Delta_i(m_i == 2), \quad (3.10)$$

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

This specification allows us to achieve an analogue of the MMNL model with inter-and-intra preference heterogeneity. For a given random parameter in the MMNL model, an additional continuous distribution is specified over choice tasks on top of the continuous distribution over decision-makers. The mean is captured by the distribution at inter-individual layer, while the variance is estimated for the distribution at the intra-individual layer. In our case, Eq. (3.10) enables the mean value of the ASC for alternative  $i$  given subclass membership  $(s, 2)$  to be maintained the same as in the corresponding “alternation-avoiders” subclass  $(s, 1)$ , which equates to  $\delta_{i,s}$ .

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 remaining  $J - 1$  non-zero ASCs. In particular, we take into account all the possible combinations for the vector  $(\delta_{1,(s,2),m_1}, \delta_{2,(s,2),m_2}, \dots, \delta_{J-1,(s,2),m_{J-1}})$ , such that all the combinations amount to  $2^{J-1}$  in total for a given individual at a given choice task. The lower part of Fig. 3.4 presents the treatment at the intra-individual layer, which the discrete mixture is taken over  $2^{J-1}$  combinations.

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 “alternation-seekers” subclass i.e.  $q = 2$ , such that:

$$\begin{aligned}
 & P(y_{nt} \mid (\delta_{(s,2)}, \beta_{(s,2)})) \\
 = & \frac{1}{2^{J-1}} \sum_{m_1=1}^2 \sum_{m_2=1}^2 \cdots \sum_{m_{J-1}=1}^2 P(y_{nt} \mid (\delta_{1,(s,2),m_1}, \delta_{2,(s,2),m_2}, \cdots, \delta_{J-1,(s,2),m_{J-1}}), \beta_s),
 \end{aligned} \tag{3.11}$$

Combined with Eqs. (3.9) - (3.11), we can get the unconditional likelihood of observing a sequence of choices for a given respondent  $n$  by replacing Eq. (3.6) with:

$$P(y_n) = \sum_{s=1}^S \pi_s \sum_{q=1}^2 \phi_q \left( \prod_{t=1}^T (P(y_{nt} \mid \delta_{(s,q)}, \beta_{(s,q)})) \right). \tag{3.12}$$

### 3.3.4 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  $\tau_{NS}$  and  $\tau_{AT}$  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. Fig. 3.5 illustrates the modelling framework of the 2L-LV-LC model. Apart from having the latent variety-seeking in explaining class membership probabilities, the two-layer structure is maintained to be the same as in Fig. 3.4. The detailed discussion over this framework is presented in the remainder of section 3.3.4.

#### 3.3.4.1 Structural equations for latent variable

We define a latent variable  $\alpha_n$  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:

$$\alpha_n = \kappa' Z_n + \eta_n, \tag{3.13}$$

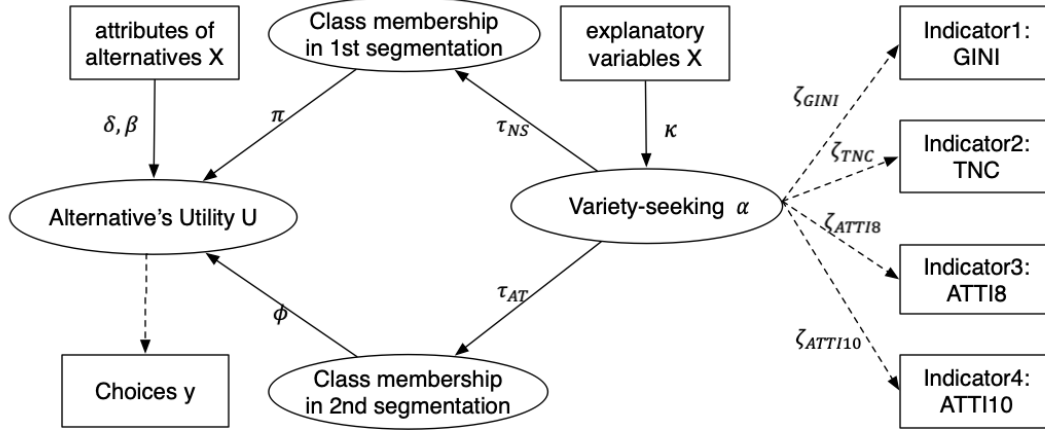


Fig. 3.5: Modelling framework of the 2L-LV-LC model.

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

### 3.3.4.2 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. (3.5) and in Eq. (3.7) as:

$$\pi_{n,1} = \frac{e^{\gamma_1 + \tau_{NS}\alpha_n}}{e^{\gamma_1 + \tau_{NS}\alpha_n} + 1}, \quad (3.14)$$

$$\pi_{n,2} = 1 - \pi_{n,1}$$

and

$$\phi_{n,1} = \frac{e^{\lambda_1 + \tau_{AT}\alpha_n}}{e^{\lambda_1 + \tau_{AT}\alpha_n} + 1}, \quad (3.15)$$

$$\phi_{n,2} = 1 - \phi_{n,1}$$

such that the class allocation probabilities  $\pi_{n,s}$  and  $\phi_{n,q}$  vary across respondents. Parameters  $\tau_{NS}$  and  $\tau_{AT}$  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  $\alpha_n$  is associated with a stronger variety-seeking tendency and class  $s = 2$  is characterised with higher propensity to adopt the new UberAIR service, then a significant negative  $\tau_{NS}$  would suggest variety-seekers have higher probabilities of falling into the class with stronger inclination to seek novelty (i.e.  $s = 2$ ); moreover, a significant negative  $\tau_{AT}$  would imply variety-seekers are more likely to belong to the class with preference heterogeneity over tasks (i.e.  $q = 2$ ).



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

$$P(y_n | \alpha_n) = \sum_{s=1}^S (\pi_{n,s} | \alpha_n) \sum_{q=1}^2 (\phi_{n,q} | \alpha_n) \left( \prod_{t=1}^T (P(y_{nt} | \delta_{(s,q)}, \beta_{(s,q)})) \right), \quad (3.16)$$

where  $P(y_{nt} | \delta_{(s,1)}, \beta_{(s,1)})$  and  $P(y_{nt} | \delta_{(s,2)}, \beta_{(s,2)})$  follow the specifications in Eq. (3.9) and Eq. (3.11), respectively.

### 3.3.4.3 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  $I_{n,\text{GINI}}$  as a measure of variety in mode choice in real world travel experience by:

$$I_{n,\text{GINI}} = \left( \sum_{k=1}^K \sum_{r=1}^K |g_{nk} - g_{nr}| \right) / \left( 2 \sum_{k=1}^K \sum_{r=1}^K g_{nr} \right) \quad (3.17)$$

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:

$$I_{n,\text{GINI}} - \overline{I_{\text{GINI}}} = \zeta_{\text{GINI}} \alpha_n + \sigma_{I_{\text{GINI}}} \xi_{I_{\text{GINI}}}, \quad (3.18)$$

with  $\overline{I_{\text{GINI}}}$  being the mean of  $I_{n,\text{GINI}}$  across individuals. Parameter  $\zeta_{\text{GINI}}$  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:

$$P(I_{n,\text{GINI}} | \alpha_n) = \frac{1}{\sigma_{I_{\text{GINI}}} \sqrt{2\pi}} \left( e^{-\frac{(I_{n,\text{GINI}} - \overline{I_{\text{GINI}}} - \zeta_{\text{GINI}} \alpha_n)^2}{2\sigma_{I_{\text{GINI}}}^2}} \right). \quad (3.19)$$

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.<sup>5</sup> The remaining two indicators are the responses to the two attitudinal statements described in section 3.2.5. As shown in Table 3.6, 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  $I_{n,\text{ATT18}}$  and  $I_{n,\text{ATT10}}$ , accordingly.

We deal with  $I_{n,\text{TNC}}$ ,  $I_{n,\text{ATT18}}$  and  $I_{n,\text{ATT10}}$  in a different way by accounting for the ordered characteristics of them, as omitting this nature would result in less 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  $\zeta_c$  to measure the impact of latent variety-seeking  $\alpha_n$  on the value of  $I_{n,c}$ . Thus, the probability of observing indicator  $I_{n,c}$  taking the value of level  $l$  ( $l \in (1, \dots, L_c)$ ) for respondent  $n$  is written as:

$$P(I_{n,c} = l \mid \alpha_n) = \frac{e^{\mu_{c,l} - \zeta_c \alpha_n}}{1 + e^{\mu_{c,l} - \zeta_c \alpha_n}} - \frac{e^{\mu_{c,l-1} - \zeta_c \alpha_n}}{1 + e^{\mu_{c,l-1} - \zeta_c \alpha_n}}, \quad (3.20)$$

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  $\alpha_n$  is written as:

$$P(I_n \mid \alpha_n) = P(I_{n,\text{GINI}} \mid \alpha_n)P(I_{n,\text{TNC}} \mid \alpha_n)P(I_{n,\text{ATT18}} \mid \alpha_n)P(I_{n,\text{ATT10}} \mid \alpha_n) \quad (3.21)$$

### 3.3.4.4 Log-likelihood function

Combining Eq. (3.16) and Eq. (3.21), 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  $\alpha_n$ ,

---

<sup>5</sup>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.

such that:

$$\begin{aligned}
& LL(y, I) \\
&= \sum_{n=1}^N \ln \int_{\alpha_n} \left( \sum_{s=1}^S (\pi_{n,s} | \alpha_n) \sum_{q=1}^2 (\phi_{n,q} | \alpha_n) \prod_{t=1}^T (P(y_{nt} | \delta_{(s,q)}, \beta_{(s,q)})) \right) P(I_n | \alpha_n) \\
& \quad f(\pi_n, \phi_n | \alpha_n) d\alpha_n.
\end{aligned} \tag{3.22}$$

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  $LL$ .

### 3.4 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 3.7. 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  $\delta_{\text{uberx}}$ ,  $\delta_{\text{uberx},1}$ ,  $\delta_{\text{uberx},2}$ , and  $\Delta_{\text{uberx}}$ ) fixed to 0. 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 the confidentiality agreement, the estimates from which the market shares could be inferred (i.e. ASCs) are not shown in Table 3.7, and the differences in individual preferences across alternatives are not discussed in this section. More precisely,  $\delta_i$  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 a post-estimation analysis

for each model, of which the results are presented in Table 3.8. 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 “alternation-seekers” subclass and a “alternation-avoiders” 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 “alternation-seekers” subclass, the choice probability for each alternative at a given choice task is obtained by averaging across all the  $2^{J-1}$  combinations (16 combinations in our case).

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 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 “★”. 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 subclasses (i.e. in model 3 and model 4), and using the example where the value is highest in the first subclass, a single “-” indicates the second highest value for that ASC, a double “--” the third highest, etc.

Table 3.7: Estimation results of choice model and class allocation models

	model 1: MNL		model 2: basic LC		model 3: 2L-LC		model 4: 2L-LV-LC				
individual#	2419		2419		2419		2419				
observation#	24190		24190		24190		24190				
parameter#	9		19		24		47				
$LL(0)$	-31414.24		-31414.24		-31414.24		whole model: -44836.06				
$LL(\text{final})$	-20740.78		-16929.74		-15625.74		SC component: -15613.48				
adj. $\rho^2$	0.3395		0.4605		0.5018		whole model: -24443.96				
AIC	41499.56		33897.48		31299.48		whole model: 0.4538				
BIC	41572.4		34051.26		31493.73		whole model: 48981.93				
	est.	t-rat.	est.	t-rat.	est.	t-rat.	est.	t-rat.			
$\beta_{\text{access}}$	-0.014	-2.04	$\beta_{\text{access},1}$	-0.099	-7.10	$\beta_{\text{access},1}$	-0.140	-4.92	$\beta_{\text{access},1}$	-0.137	-4.88
$\beta_{\text{egress}}$	-0.033	-4.28	$\beta_{\text{egress},1}$	-0.122	-7.93	$\beta_{\text{egress},1}$	-0.170	-6.10	$\beta_{\text{egress},1}$	-0.169	-6.12
$\beta_{\text{flight}}$	-0.013	-3.05	$\beta_{\text{flight},1}$	-0.078	-8.90	$\beta_{\text{flight},1}$	-0.117	-6.80	$\beta_{\text{flight},1}$	-0.115	-6.81
$\beta_{\text{invehi}}$	-0.017	-8.18	$\beta_{\text{invehi},1}$	-0.040	-11.38	$\beta_{\text{invehi},1}$	-0.058	-7.22	$\beta_{\text{invehi},1}$	-0.057	-7.27
$\beta_{\text{cost}}$	-1.171	-17.10	$\beta_{\text{cost},1}$	-3.530	-11.71	$\beta_{\text{cost},1}$	-6.670	-15.05	$\beta_{\text{cost},1}$	-6.654	-14.59
$\delta_{\text{car}}$	*	*	$\delta_{\text{car},1}$	*	*	$\delta_{\text{car},1}$	*	*	$\delta_{\text{car},1}$	*	*
$\delta_{\text{transit}}$	*	*	$\delta_{\text{transit},1}$	*	*	$\delta_{\text{transit},1}$	*	*	$\delta_{\text{transit},1}$	*	*
$\delta_{\text{uberx}}$	0.000	NA	$\delta_{\text{uberx},1}$	0.000	NA	$\delta_{\text{uberx},1}$	0.000	NA	$\delta_{\text{uberx},1}$	0.000	NA
$\delta_{\text{uberpool}}$	*	*	$\delta_{\text{uberpool},1}$	*	*	$\delta_{\text{uberpool},1}$	*	*	$\delta_{\text{uberpool},1}$	*	*
$\delta_{\text{uberair}}$	*	*	$\delta_{\text{uberair},1}$	*	*	$\delta_{\text{uberair},1}$	*	*	$\delta_{\text{uberair},1}$	*	*
			$\beta_{\text{access},2}$	-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
			$\delta_{\text{uberx},2} - \delta_{\text{uberx},1}$	0.000	NA	$\delta_{\text{uberx},2} - \delta_{\text{uberx},1}$	0.000	NA	$\delta_{\text{uberx},2} - \delta_{\text{uberx},1}$	0.000	NA
			$\delta_{\text{uberpool},2} - \delta_{\text{uberpool},1}$	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

(Continued on the next page)

**Table 3.7:** Estimation results of choice model and class allocation models (continued)

model 1: MNL		model 2: basic LC		model 3: 2L-LC		model 4: 2L-LV-LC				
est.	t-rat.	est.	t-rat.	est.	t-rat.	est.	t-rat.			
		$\gamma_1$	0.280	3.78	$\gamma_1$	0.452	6.54	$\gamma_1$	0.444	5.95
		-			-	-		$\tau_{NS}$	-0.523	-9.24
					$\lambda_1$	0.738	11.49	$\lambda_1$	0.798	11.61
					-	-		$\tau_{AT}$	-0.325	-5.27
					$\Delta_{car}$	3.315	10.00	$\Delta_{car}$	3.332	9.81
					$\Delta_{transit}$	11.205	9.45	$\Delta_{transit}$	11.244	9.32
					$\Delta_{uberx}$	0.000	NA	$\Delta_{uberx}$	0.000	NA
					$\Delta_{uberpool}$	-5.008	-10.25	$\Delta_{uberpool}$	-5.037	-10.07
					$\Delta_{uberair}$	8.761	23.35	$\Delta_{uberair}$	8.851	22.97
								$\zeta_{ATT18}$	1.616	12.78
								$\zeta_{ATT10}$	1.555	12.69
								$\zeta_{GINI}$	-0.068	-13.17
								$\zeta_{TNC}$	1.111	12.64
								$\sigma_{GINI}$	0.206	75.22
								$\mu_{ATT18\_1}$	-3.250	-22.72
								$\mu_{ATT18\_2}$	-1.145	-14.42
								$\mu_{ATT18\_3}$	0.794	12.10
								$\mu_{ATT18\_4}$	3.004	22.58
								$\mu_{ATT10\_1}$	-3.500	-23.46
								$\mu_{ATT10\_2}$	-2.246	-21.05
								$\mu_{ATT10\_3}$	0.121	2.01
								$\mu_{ATT10\_4}$	1.991	20.71
								$\mu_{TNC\_noexperience}$	-0.850	-16.18
								$\mu_{TNC\_one}$	0.671	11.82
								$\mu_{TNC\_two}$	5.226	22.10
								$\kappa_{age}$	-1.185	-12.87
								$\kappa_{income}$	0.213	10.16
								$\kappa_{female}$	-0.660	-11.23
								$\kappa_{delay}$	0.200	3.79
								$\kappa_{vehicles}$	-0.094	-3.36

Table 3.8: Value-of-time (VoT) estimates and choice probabilities

parameter	model 1	model 2			model 3			model 4				
	MNL	basic LC			2L-LC			2L-LV-LC				
#	9	19			24			47				
$LL(\text{whole})$	-20740.78	-16929.74			-15625.74			-24443.96				
$LL(\text{SC})$								-15613.48				
$\rho^2$	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		
VoT (\$/h)												
access	15.07	36.20	13.43	26.40	27.05	24.74	26.15	26.66	25.07	25.99		
egress	35.97	44.77	32.28	39.40	32.93	36.14	34.18	32.89	36.78	34.54		
flight	14.27	28.36	15.32	22.75	22.57	18.11	20.83	22.22	18.53	20.65		
invehicle	19.19	14.51	15.87	15.09	11.30	18.14	13.96	11.15	18.16	14.12		
Market share changes					subclass (1,1)	subclass (1,2)	subclass (2,1)	subclass (2,2)	subclass (1,1)	subclass (1,2)	subclass (2,1)	subclass (2,2)
					avoid	seek	avoid	seek	avoid	seek	avoid	seek
car	*	*	-		*	-	-	-	*	-	-	-
transit	*	*	-		*	-	-	-	*	-	-	-
UberX	*	*	-		*	-	-	-	*	-	-	-
UberPool	*	*	+		*	+	+++	++	*	+	+++	++
UberAir	*	*	+		*	++	+	+++	*	++	+	+++

### 3.4.1 Model 1: MNL model

As shown in Table 3.7, people are found to present almost twice as strong a sensitivity towards egress time (est.=-0.033,  $t$ -rat.=-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 3.8. Egress time has the highest value, with \$35.97/h for the whole sample.

### 3.4.2 Model 2: Basic LC model

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

#### 3.4.2.1 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.

#### 3.4.2.2 Class-specific results

Compared to model 1, model 2 illustrated preference heterogeneity across respondents. As shown in Table 3.7, the constant  $\gamma_1$  (est.=0.280,  $t$ -rat.=3.78) in the class allocation function implies a probability of 56.95% (i.e.  $\frac{\exp(0.280)}{1+\exp(0.280)} = 56.95\%$ ) for respondents to fall into Class 1 and a probability of 43.05% (i.e.  $1 - 56.95\% = 43.05\%$ ) 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 3.8, we can see that Class 2 shows much lower VoT for all the time components, except for in-vehicle time 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 3.8, 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.

### 3.4.3 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 many differences against model 2. However, model 3 can give more insight into preference patterns and market segmentation (see section 3.4.3.4).

#### 3.4.3.1 Model estimates

We first look at the sensitivity parameters at the inter layer in Table 3.7. 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,  $t$ -rat.=−1.51, by delta method calculation).

Turning to the model estimates at the intra layer, the significant estimates of the shift terms  $\Delta$  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  $\gamma_1$  (est.=0.452,  $t$ -rat.=6.54) results in a generic probability to fall into either Class 1 (i.e.  $\frac{\exp(0.452)}{1+\exp(0.452)} = 61.11\%$ ) or Class 2 (i.e.  $1 - 61.11\% = 38.89\%$ ) across respondents. Parameter  $\lambda_1$  (est.=0.738,  $t$ -rat.=11.49) leads to a generic probability of 67.66% (i.e.  $\frac{\exp(0.738)}{1+\exp(0.738)} = 67.66\%$ ) in belonging to a “alternation-avoiders” subclass and 32.34% (i.e.  $1 - 67.66\% = 32.34\%$ ) in being assigned to a “alternation-seekers” subclass.

### 3.4.3.2 Value-of-time results

Regarding the VoT patterns shown in Table 3.8, 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.

### 3.4.3.3 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 “alternation-avoiders” and “alternation-seekers” 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 “alternation-avoiders” subclasses (1, 1) and (2, 1) have higher average chosen probabilities (i.e. 66.04% and 55.88%) than “alternation-seekers” subclasses (1, 2) and (2, 2) (i.e. 45.85% and 30.30%), respectively. This suggests that respondents who fall into the “alternation-seekers” class are associated with less deterministic choices, which is in accordance with our expectation.

### 3.4.3.4 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):  $61.11\% \times 67.66\% = 41.35\%$ 
  - Low tendency to try new modes including UberAIR (i.e. avoid novelty)
  - Stable preference across choice tasks (i.e. avoid alternation)

- Subclass (1, 2):  $61.11\% \times 32.34\% = 19.77\%$ 
  - Low tendency to try new modes including UberAIR (i.e. avoid novelty)
  - Unstable preference across choice tasks (i.e. seek alternation)
- Subclass (2, 1):  $38.89\% \times 67.66\% = 26.31\%$ 
  - High tendency to try new modes including UberAIR (i.e. seek novelty)
  - Stable preference across choice tasks (i.e. avoid alternation)
- Subclass (2, 2):  $38.89\% \times 32.34\% = 12.58\%$ 
  - High tendency to try new modes including UberAIR (i.e. seek novelty)
  - Unstable preference across choice tasks (i.e. seek alternation)

#### 3.4.4 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 and VoT results. Herein, we only discuss the unique characteristics of model 4, i.e. the impact of latent variety-seeking.

##### 3.4.4.1 Variety-seeking in measurement model component

We first look at the estimates in the measurement equations which are shown below the dashed line in Table 3.7. 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  $\zeta_{ATTI8}$ ,  $\zeta_{ATTI10}$  and  $\zeta_{TNC}$ , we can see that an increase in the latent variable  $\alpha$  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  $\zeta_{GINI}$  implies that a stronger  $\alpha$  is associated with a lower Gini coefficient, suggesting less inequality and less uniqueness in mode choice experience. As mentioned in section 3.3.4.3, the indicator “GINI” focuses on “inequality” in exposure to different types of modes, while indicator “TNC” stresses more on the diversity of usage within the category of ride-sourcing providers. A Pearson correlation test suggests that these two indicators are significantly negatively correlated (corr: -0.44,  $p$ -value=0.000). This means that more equal exposure to various modes (i.e. smaller GINI value) can

be related to wider usage of ride-sourcing companies (i.e. higher TNC value). One would expect some degree of correlation across the indicators as we expect them to represent the same underlying behavioural trait of variety seeking. The correlation is sufficiently low to warrant the use of four separate indicators. We think one way to further improve the model specification is to add a correlation component for the two measurement equations between GINI and TNC.

#### 3.4.4.2 Variety-seeking in choice model component

Now we jointly examine the role of the latent variable  $\alpha$  in the class allocation functions in the choice model component and in the measurement model component. As shown above the dashed line in Table 3.7, the constants  $\gamma_1$  and  $\lambda_1$  at the inter-individual layer are very close to those in model 3. The negative and significant  $\tau_{NS}$  (est.=-0.523,  $t$ -rat.=-9.24) means that a higher value of the latent variable  $\alpha$  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  $\tau_{AT}$  (est.=-0.325,  $t$ -rat.=-5.27) implies a decrease in probability of belonging to “alternation-avoiders” subclasses (1, 1) and (2, 1) with an increase in the latent variable  $\alpha$ . Hence, the probabilities of falling in a given subclass vary across respondents in model 4, depending on the value of  $\alpha$ . All these contribute to the inference that the latent variable  $\alpha$  can indeed be interpreted as “variety-seeking”, such that a larger value in  $\alpha$  corresponds to a stronger variety-seeking tendency.

Combining the interpretation of the latent variable  $\alpha$  and the class allocation functions, our hypothesis can be confirmed. 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 propensities to belong to the “alternation-seekers” 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 3.4.3.4 can be retrieved by

model 4. The allocation probability averaged over the sample for each subclass in model 4 is 42.19% for subclass (1,1), 17.89% for subclass (1,2), 26.21% for subclass (2,1) and 13.71% for subclass (2,2). 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.

To more explicitly illustrate the impact of the novelty-seeking aspect and alternation aspect of variety-seeking, we compare the choice probability (i.e. market share) of the new UberAIR alternative across different (sub)classes, when the latent variety-seeking  $\alpha_n$  takes the mean value of the distribution (i.e.  $\alpha_n = 0$ ). Generally, we can find that the ratio of the market share of air taxi in the novelty-seeker class to the novelty-avoider class is approximately 1.5:1, and the ratio of the market share of air taxi in the subclasses with alternation effect to the subclasses without alternation effect is around 2.8:1. This suggests that both effects are of significant size. We also can find a probability of nearly 60% to be affected by novelty-seeking and (or) alternation. Specifically, there would be a probability of around 39% to seek novelty and a probability of 31% to exhibit the alternation effect, implying that the two aspects of variety-seeking are both relevant in mode choice decisions and that variety-seeking is relatively more driven/reflected by novelty-seeking aspect. The calculations of these proportions are shown in the Appendix.

#### 3.4.4.3 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. (3.13). The detailed specification of the structural equation in this final adopted model representation is shown as:

$$\begin{aligned} \alpha_n = & \kappa_{\text{age}} \left( \frac{Z_{n,\text{age}} - \bar{Z}_{\text{age}}}{\bar{Z}_{\text{age}}} \right) + \kappa_{\text{income}} \left( \frac{Z_{n,\text{income}} - \bar{Z}_{\text{income}}}{\bar{Z}_{\text{income}}} \right) \\ & + \kappa_{\text{female}} (Z_{n,\text{female}} - \bar{Z}_{\text{female}}) + \kappa_{\text{delay}} (Z_{n,\text{delay}} - \bar{Z}_{\text{delay}}), \\ & + \kappa_{\text{vehicles}} (Z_{n,\text{vehicles}} - \bar{Z}_{\text{vehicles}}) + \eta_n \end{aligned} \quad (3.23)$$

where  $\bar{Z}_z$  represents the mean value of explanatory variable  $z$  over the sample. 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  $\kappa$  in Table 3.7 show how these explanatory variables affect the value of latent variety-seeking. As expected, the negative  $\kappa_{\text{age}}$ ,  $\kappa_{\text{female}}$  and  $\kappa_{\text{vehicles}}$  show that older people, female respondents and people with more vehicles are characterised by weaker variety-seeking tendencies, whereas the positive  $\kappa_{\text{income}}$  and  $\kappa_{\text{delay}}$  suggest that people with more income and who have experienced delay on the same trip in the past have stronger variety-seeking tendencies.

We acknowledge that the current specification of the structural equation might lead to endogeneity issue as the number of owned vehicles could also be determined by variety-seeking tendencies. This specification can be further improved by, for instance, removing the variable that causes the concern from the structural equation. We will leave this for future research.

### 3.4.5 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,  $\rho^2$  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.

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 a better fit than a corresponding reduced form model without latent variables. However, model 3 presented in our study is not the corresponding reduced form mixed logit model for model 4. This is because 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.

## 3.5 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

### 3.5. Conclusions

to the next dimension for shared air travel, i.e. Urban 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 a 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.

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 tendencies on mode choice behaviour. We established a new latent class model with two layers of preference heterogeneity, where variety-seeking was treated as a latent variable. This model was proposed based on the assumption that the novelty-seeking aspect of variety-seeking can be reflected through the choice probability of the new mode, while the alternation-seeking aspect of variety-seeking can be reflected via the stability of preferences across choice tasks. At the inter-individual layer, respondents were first probabilistically segmented into two classes, one of which exhibiting higher propensity to adopt the new UberAIR service than the other (i.e. novelty-seekers class and novelty-avoiders class). Each class was further probabilistically segmented into two subclasses - one subclass with consistent and stable preferences throughout choice tasks and another subclass with preference variation across choice tasks (i.e. alternation-avoiders subclass and alternation-seekers subclass). Intra-individual preference heterogeneity was accommodated for the “alternation-seekers” subclasses to control for the alternation aspect of variety-seeking through an additional layer of the 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 re-

duce the computational burden. Particularly, in each step of segmentation at the inter-individual layer, the class allocation probability was a function of the latent variable of variety-seeking. With step-specific parameters in each class allocation model, the role of novelty-seeking aspect and alternation aspect can be captured separately.

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 preferences 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 journey in the past have stronger variety-seeking tendencies. In the meantime, those variety-seekers were also observed to show stronger agreement to 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 the 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 a more complex specification. Nevertheless, it would be worth testing the model with other alternative estimation methods, e.g. EM algorithms ([Train, 2008](#)). It would then facilitate testing models which allow a broader spectrum of novelty-seeking or alternation-seeking, i.e. specifying more than two groups in each segmentation rather than having a binary classification. Moreover, respondents' risk perception and risk-taking tendencies may play a role in determining whether to adopt air taxi, especially given that this new mode is not ground-based and requires passengers to remain in a small and enclosed space. A recent study by [Rothfeld et al. \(2020\)](#) points out attitudinal factors like concern for the environment and safety are both relevant in deciding



whether to adopt the new mode of air taxi. Hence, this research can be further improved if the impact of these other underlying psychological factors can be accounted for together with the impact of variety-seeking, especially given that some relevant attitudinal responses are available in our data.

We believe that the work conducted in this study is relevant not just to a transport setting but to 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. Furthermore, the impact of social networks is worth more research effort. While some people have a stronger desire for distinction among populations, others are more prone to be positively affected by their social network and imitate other people’s behaviour. Improving understanding of this issue can enable us to better explain whether, why and when an adoption decision would be made at the individual level. Finally, we have already found that variety-seekers are more likely to be attracted to adopt a new mode at an early stage, they might in the meantime be less likely to stick to using the new mode over time. This requires further investigation using longitudinal RP data to explore whether people behave in this manner in the real-world. Hence, 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 long 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](#)).

## Acknowledgements

Fangqing Song acknowledges the support of the China Scholarship Council while Stephane Hess was supported by the European Research Council through the consolidator grant 615596-DECISIONS. The authors are thankful to RSG and Uber for providing the stated choice data.

## Appendix

1. Given that  $\gamma_1 = 0.444$  and  $\lambda_1 = 0.798$ , the proportions of different segments of individuals when  $\alpha_n$  takes the mean value (i.e.  $\alpha_n = 0$ ) can be calculated

Chapter 3. Fancy sharing an air taxi? Uncovering the impact of variety seeking on the demand for new shared mobility services

as below:

- Novelty-seeking:

$$1 - \frac{\exp(0.444)}{(1+\exp(0.444))} = 0.39$$

- Seek alternation (i.e. accounting for intra-individual preference heterogeneity):

$$1 - \frac{\exp(0.798)}{(1+\exp(0.798))} = 0.31$$

- Affected by novelty-seeking and (or) alternation (excludes the part that is affected by neither aspects):

$$1 - \frac{\exp(0.444)}{(1+\exp(0.444))} \times \frac{\exp(0.798)}{(1+\exp(0.798))} = 0.58$$

## References

- Agatz, N., Erera, A., Savelsbergh, M., Wang, X., 2012. Optimization for dynamic ride-sharing: A review. *European Journal of Operational Research* 223 (2), 295–303.
- Alemi, F., Circella, G., Handy, S., Mokhtarian, P., 2018. What influences travelers to use uber? exploring the factors affecting the adoption of on-demand ride services in california. *Travel Behaviour and Society* 13, 88–104.
- Baik, H., Trani, A. A., Hinze, N., Swingle, H., Ashiabor, S., Seshadri, A., 2008. Forecasting model for air taxi, commercial airline, and automobile demand in the united states. *Transportation Research Record* 2052 (1), 9–20.
- Bardhi, F., Eckhardt, G. M., 2012. Access-based consumption: The case of car sharing. *Journal of consumer research* 39 (4), 881–898.
- Becker, F., Danaf, M., Song, X., Atasoy, B., Ben-Akiva, M., 2018. Bayesian estimator for logit mixtures with inter-and intra-consumer heterogeneity. *Transportation Research Part B: Methodological* 117, 1–17.
- Ben-Akiva, M., Walker, J., Bernardino, A. T., Gopinath, D. A., Morikawa, T., Polydoropoulou, A., 2002. Integration of choice and latent variable models. *Perpetual motion: Travel behaviour research opportunities and application challenges*, 431–470.
- Borgers, A., Van Der Heijden, R., Timmermans, H., 1989. A variety seeking model of spatial choice-behaviour. *Environment and Planning A* 21 (8), 1037–1048.
- Boyd, J. H., Mellman, R. E., 1980. The effect of fuel economy standards on the us automotive market: an hedonic demand analysis. *Transportation Research Part A: General* 14 (5-6), 367–378.
- Cardell, N. S., Dunbar, F. C., 1980. Measuring the societal impacts of automobile downsizing. *Transportation Research Part A: General* 14 (5-6), 423–434.
- Chintagunta, P. K., 1998. Inertia and variety seeking in a model of brand-purchase timing. *Marketing Science* 17 (3), 253–270.
- Cramer, J., Krueger, A. B., 2016. Disruptive change in the taxi business: The case of uber. *American Economic Review* 106 (5), 177–82.

## References

- Daly, A., Hess, S., de Jong, G., 2012a. Calculating errors for measures derived from choice modelling estimates. *Transportation Research Part B: Methodological* 46 (2), 333–341.
- Daly, A., Hess, S., Patrui, B., Potoglou, D., Rohr, C., 2012b. Using ordered attitudinal indicators in a latent variable choice model: a study of the impact of security on rail travel behaviour. *Transportation* 39 (2), 267–297.
- Dekker, T., Hess, S., Brouwer, R., Hofkes, M., 2016. Decision uncertainty in multi-attribute stated preference studies. *Resource and Energy Economics* 43, 57–73.
- DeMaio, P., 2009. Bike-sharing: History, impacts, models of provision, and future. *Journal of public transportation* 12 (4), 3.
- Dias, F. F., Lavieri, P. S., Garikapati, V. M., Astroza, S., Pendyala, R. M., Bhat, C. R., 2017. A behavioral choice model of the use of car-sharing and ride-sourcing services. *Transportation* 44 (6), 1307–1323.
- Dong, Y., Wang, S., Li, L., Zhang, Z., 2018. An empirical study on travel patterns of internet based ride-sharing. *Transportation research part C: emerging technologies* 86, 1–22.
- EASA, 2018. Flying in the EU: Ops is in the air. [https://www.easa.europa.eu/sites/default/files/dfu/EASA\\_GA\\_LEAFLET\\_AIR\\_OPS\\_2018\\_EN.pdf](https://www.easa.europa.eu/sites/default/files/dfu/EASA_GA_LEAFLET_AIR_OPS_2018_EN.pdf), accessed: 2019-04-15.
- El Zarwi, F., Vij, A., Walker, J. L., 2017. A discrete choice framework for modeling and forecasting the adoption and diffusion of new transportation services. *Transportation Research Part C: Emerging Technologies* 79, 207–223.
- Fu, M., Rothfeld, R., Antoniou, C., 2018. Exploring preferences for transportation modes in an urban air mobility environment: Munich case study. *Transportation Research Record*, 0361198119843858.
- Furuhata, M., Dessouky, M., Ordóñez, F., Brunet, M.-E., Wang, X., Koenig, S., 2013. Ridesharing: The state-of-the-art and future directions. *Transportation Research Part B: Methodological* 57, 28–46.
- Givon, M., 1984. Variety seeking through brand switching. *Marketing Science* 3 (1), 1–22.
- Goyal, R., 2018. Urban air mobility (uam) market study.

- Gupta, S., Chintagunta, P. K., 1994. On using demographic variables to determine segment membership in logit mixture models. *Journal of Marketing Research* 31 (1), 128–136.
- Ha, J., Jang, S. S., 2013. Variety seeking in restaurant choice and its drivers. *International Journal of Hospitality Management* 32, 155–168.
- Hensher, D. A., 2018. Tackling road congestion—what might it look like in the future under a collaborative and connected mobility model? *Transport policy* 66, A1–A8.
- Hess, S., Giergiczny, M., 2015. Intra-respondent heterogeneity in a stated choice survey on wetland conservation in belarus: first steps towards creating a link with uncertainty in contingent valuation. *Environmental and Resource Economics* 60 (3), 327–347.
- Hess, S., Palma, D., 2019. Apollo: a flexible, powerful and customisable freeware package for choice model estimation and application.
- Hess, S., Rose, J. M., 2009. Allowing for intra-respondent variations in coefficients estimated on repeated choice data. *Transportation Research Part B: Methodological* 43 (6), 708–719.
- Hess, S., Shires, J., Jopson, A., 2013. Accommodating underlying pro-environmental attitudes in a rail travel context: application of a latent variable latent class specification. *Transportation Research Part D: Transport and Environment* 25, 42–48.
- Hess, S., Spitz, G., Bradley, M., Coogan, M., 2018. Analysis of mode choice for intercity travel: Application of a hybrid choice model to two distinct us corridors. *Transportation Research Part A: Policy and Practice* 116, 547–567.
- Hess, S., Stathopoulos, A., 2013. Linking response quality to survey engagement: a combined random scale and latent variable approach. *Journal of choice modelling* 7, 1–12.
- Hess, S., Train, K. E., 2011. Recovery of inter-and intra-personal heterogeneity using mixed logit models. *Transportation Research Part B: Methodological* 45 (7), 973–990.
- Holden, J., Goel, N., 2016. *Fast-forwarding to a future of on-demand urban air transportation*. San Francisco, CA.

## References

- INRIX, 2018. Urban mobility scorecard. <http://inrix.com/scorecard/>, accessed: 2019-04-01.
- Jin, S. T., Kong, H., Wu, R., Sui, D. Z., 2018. Ridesourcing, the sharing economy, and the future of cities. *Cities* 76, 96–104.
- Joshi, A., DeLaurentis, D., Peeta, S., Agusdinata, D. B., 2014. Integrated framework and assessment of on-demand air service in multimodal context. *Journal of Aircraft* 51 (2), 402–411.
- Kamakura, W. A., Russell, G. J., 1989. A probabilistic choice model for market segmentation and elasticity structure. *Journal of marketing research* 26 (4), 379–390.
- Koopman, C., Dourado, E., 2017. Defining common carriers: Flight sharing, the faa, and the future of aviation.
- McAlister, L., Pessemier, E., 1982. Variety seeking behavior: An interdisciplinary review. *Journal of Consumer research* 9 (3), 311–322.
- McFadden, D., et al., 1973. Conditional logit analysis of qualitative choice behavior.
- Motoaki, Y., Daziano, R. A., 2015. A hybrid-choice latent-class model for the analysis of the effects of weather on cycling demand. *Transportation Research Part A: Policy and Practice* 75, 217–230.
- Office for National Statistics, 2019. Road transport and air emissions. <https://www.ons.gov.uk/economy/environmentalaccounts/articles/roadtransportandairemissions/2019-09-16>, accessed: 2019-09-16.
- Park, Y., Ha, H.-K., 2006. Analysis of the impact of high-speed railroad service on air transport demand. *Transportation Research Part E: Logistics and Transportation Review* 42 (2), 95–104.
- Peeta, S., Paz, A., DeLaurentis, D., 2008. Stated preference analysis of a new very light jet based on-demand air service. *Transportation Research Part A: Policy and Practice* 42 (4), 629–645.
- Pu, D., Trani, A. A., Hinze, N., 2014. Zip vehicle commuter aircraft demand estimate: A multinomial logit mode choice model. In: 14th AIAA Aviation Technology, Integration, and Operations Conference. p. 2411.

- Román, C., Espino, R., Martín, J. C., 2007. Competition of high-speed train with air transport: The case of madrid–barcelona. *Journal of Air Transport Management* 13 (5), 277–284.
- Rothfeld, R., Straubinger, A., Fu, M., Al Haddad, C., Antoniou, C., 2020. Urban air mobility. In: *Demand for Emerging Transportation Systems*. Elsevier, pp. 267–284.
- Shaheen, S., Cohen, A., Zohdy, I., 2016. Shared mobility: current practices and guiding principles. Tech. rep.
- Shaheen, S. A., Guzman, S., Zhang, H., 2010. Bikesharing in europe, the americas, and asia: past, present, and future. *Transportation Research Record* 2143 (1), 159–167.
- Song, F., Hess, S., Dekker, T., 2018. Accounting for the impact of variety-seeking: Theory and application to hsr-air intermodality in china. *Journal of Air Transport Management* 69, 99–111.
- Train, K. E., 2008. Em algorithms for nonparametric estimation of mixing distributions. *Journal of Choice Modelling* 1 (1), 40–69.
- U.S. Census Bureau, 2018. 2013-2017 American Community Survey 5-Year Estimates. [https://factfinder.census.gov/faces/nav/jsf/pages/community\\_facts.xhtml](https://factfinder.census.gov/faces/nav/jsf/pages/community_facts.xhtml), accessed: 2019-04-21.
- Vij, A., Walker, J. L., 2016. How, when and why integrated choice and latent variable models are latently useful. *Transportation Research Part B: Methodological* 90, 192–217.
- Walker, J. L., Ben-Akiva, M., Bolduc, D., 2007. Identification of parameters in normal error component logit-mixture (neclm) models. *Journal of Applied Econometrics* 22 (6), 1095–1125.





## Chapter 4

# A joint model for stated choice and best worst scaling data using latent attribute importance: application to high-speed rail

Fangqing Song<sup>1</sup>, Stephane Hess<sup>1</sup> & Thijs Dekker<sup>1</sup>

## Abstract

*The paper is conducted in the context of a mode choice experiment when a new mode is introduced. Stated choice (SC) data and two types of Best-worst scaling (BWS) data (i.e. case 1 and case 2) are collected from the same respondents. We mix survey methods rather than using a longer SC survey to better understand choice behaviour whilst avoiding the additional cognitive burden caused by additional SC tasks. Although BWS data has been increasingly collected alongside stated choice (SC) data, little is known about the relationships between BWS responses and SC responses at the level of individual respondents. Also, little effort has been made to jointly exploit the behavioural information from BWS data and SC data to improve the understanding of choices. This paper proposes a joint model which links the BWS and SC data through the notion of latent attribute importance. The modelling results show that people perceive attribute importance in a relatively consistent way across different survey methods, i.e. a person who perceives higher importance from an attribute is associated with a stronger sensitivity to that attribute in SC tasks, more weight on the same attribute in BWS1 tasks and wider gaps in terms of attractiveness between levels for the same attribute - in comparison to other individuals. This consistency shows that the additional behavioural information gained from BWS1 and BWS2 data can be simultaneously estimated together with SC data within a single modelling framework to improve the explanation of the choices and the role of the*

---

<sup>1</sup>Institute for Transport Studies and Choice Modelling Centre, University of Leeds (UK)

*attributes. Nevertheless, we have not found a one-to-one relationship between different survey methods. As such, there remain some differences in how attributes are evaluated between SC, BWS1 and BWS2 surveys.*

**Key words:** Stated choice, Best-worst scaling, Attribute importance, MaxDiff model, Integrated Choice and Latent Variable model

## 4.1 Introduction

Many new travel modes have emerged in recent years. Studies aimed at understanding individuals' choice behaviour and the travel demand for novel alternatives have predominantly relied on stated-choice (SC) data, where a respondent chooses his/her most preferred alternative in each hypothetical scenario. A new travel mode is usually characterised with some new attributes which individuals are not familiar with. Therefore, it is expected to exploit more information on these new attributes from each respondent. However, increasing the number of tasks of a SC survey might increase the cognitive burden of respondents. Thus, it is necessary to gain additional behavioural information through other types of preference elicitation methods to help us better understand how people make choices in the context of new modes and the role that these new attributes play. This combination of data sources can be helpful to improve the robustness of policy recommendations, particularly when the number of tasks that can be used in an SC experiment is limited due to the cognitive burden of the choice tasks. This can especially be the case when many attributes are involved (Bradley and Daly, 1994; Carlsson, 2003; Pullman et al., 1999).

Recently, a limited number of travel behaviour studies have adopted the best-worst scaling (BWS) approaches as alternative preference elicitation methods (e.g. Beck and Rose, 2016; Beck et al., 2017; Dumont et al., 2015; Hensher et al., 2015). The BWS approaches originate in marketing and the majority of its applications can be found in the marketing and health literature. In BWS, respondents are asked to in each task select the best and worst options. Different formats of this exist. BWS Case 1 surveys ask respondents to identify, in each "choice" screen, the most and least important attributes per se without a focus on the actual levels (e.g. Auger et al., 2007; Finn and Louviere, 1992; Marti, 2012). BWS Case 2 surveys ask respondents to identify the most and least important attribute levels (e.g. Coast et al., 2006; Dyachenko et al., 2014). While BWS Case 1 measures the relative weights of attributes, BWS Case 2 measures the relative attractiveness of attribute levels across different attributes. Like SC surveys, BWS Case 3 surveys also compare amongst different alternatives, each

described by a combination of attribute levels; but BWS Case 3 surveys need respondents to identify both the most and the least preferred alternatives in each choice occasion. Comparisons between SC and BWS case 3 data can be found in the work of [Giergiczny et al. \(2017\)](#) and [Petrolia et al. \(2018\)](#).

This research is conducted in the context where a new travel mode, i.e. high-speed rail(HSR)-air intermodality, is introduced. Since our interest is in predicting choices, we adopt a traditional SC survey, as it allows us to analyse how respondents make trade-offs between attributes and forecast travel demand within multi-alternative settings. BWS Case 3 survey is not adopted for this purpose as it combines best and worst whereas existing studies suggest that those are two different things ([Giergiczny et al., 2017](#); [Rose, 2014](#)).<sup>2</sup> In addition, BWS Case 1 and BWS Case 2 surveys are used as these two methods can reflect how individuals are influenced by different attributes in relatively more direct manners in single-alternative settings. As such, BWS Case 1 and BWS Case 2 data serves as additional behavioural information to help in better explaining the role of specific attributes in these choice decisions.<sup>3</sup>

This paper aims at exploring approaches to synthesise SC, BWS Case 1 and Case 2 data within a same modelling framework to improve the explanation of choices with the help of the supplementary information obtained from BWS Case 1 and Case 2 data. A key question in achieving this target, which has not been addressed in the literature, is whether the extent to which respondents weight attributes in a BWS Case 1 survey and rank attribute levels in a BWS Case 2 survey is consistent with how those same attributes and levels influence the choices in a SC survey. A high level of correspondence between the different data sources would imply greater exploitation of the auxiliary BWS Case 1 and Case 2 data in enhancing the explanation of stated choices and building a more robust evidence base for policy recommendations.

The majority of studies comparing SC data and BWS Case 1 and (or) Case 2 data have been conducted at the sample level (e.g. [Louviere and Islam, 2008](#); [Potoglou et al., 2011](#)). Only [Balbontin et al. \(2015\)](#) and [Beck et al. \(2017\)](#) have jointly analysed SC and BWS Case 2 data. However, there are some remaining limitations associated with these two joint estimation studies. The former lacks of flexibility in model specification as it assumes the impact of an attribute level

---

<sup>2</sup>We thank one reviewer for pointing out the latest work by Hawkins, Islam and Marley (2018) that suggested selecting best and selecting the worst are actually “the same”.

<sup>3</sup> BWS approaches outweigh rating or ranking method as it can take advantage of respondents’ tendency of responding more consistently and accurately to extreme options on an underlying scale from a relatively small choice set([Marley and Louviere, 2005](#)). Thus conventional rating or ranking method is not used to help explain choices in our study.

in the SC tasks to be equal (or a function of) the impact of the same attribute level revealed in the BWS Case 2 data. The latter directly incorporated the average impact over different attribute levels from BWS Case 2 data to help explain choices in SC data and thereby exposes itself to potential endogeneity biases. Meanwhile, the joint analysis of SC data with BWS Case 1 data has not yet been explored.<sup>4</sup>

In this paper, we put forward a flexible approach to jointly estimate SC, BWS Case 1 and BWS Case 2 data at the individual level while overcoming the shortcomings in the literatures. This approach is based on the assumption that responses to BWS Case 1, BWS Case 2 and SC tasks are all driven by a common underlying factor of perceived *attribute importance*. We develop an Integrated Choice and Latent Variable (ICLV) model (Ben-Akiva et al., 2002) where each attribute is associated with a latent variable of *attribute importance*. The notion of *attribute importance* has previously been put forward to challenge the decision heuristic of attribute non-attendance (Hensher, 2006; Hensher et al., 2005; Hensher and Rose, 2009), arguing that some people actually perceive reduced importance for an attribute in making stated choices rather than completely ignoring it even if the respondents stated that they did not take the associated attribute into account (Campbell et al., 2011; Hess and Hensher, 2010; Hess et al., 2013). Our work adopts a similar strategy as Hess and Hensher (2013), who use latent *attribute importance* to simultaneously explain the responses to SC tasks and the responses to selected indicators, including binary stated attribute attendance and stated attribute rankings. In our proposed model, the indicators are replaced by BWS Case 1 and Case 2 data.

We apply the proposed model in the context of a new HSR-air intermodal service in China. This new service facilitates people's long-distance travel by allowing passengers to jointly use HSR and flight to make a journey without the hassle of purchasing train tickets and flights separately. As expected, we find a certain degree of correspondence among the behaviour in the stated choice scenarios, BWS Case 1 exercises and BWS Case 2 exercises. That is, for a given attribute, people who perceive stronger importance of an attribute derive higher marginal utility from that attribute in SC tasks, attach higher weight on that attribute in BWS1 tasks, and are more sensitive to changes in level values of that attribute in BWS2 tasks - in comparison to other people. This correlation suggests that the supplementary BWS1 and BWS2 tasks can indeed bring about desired additional information and help better explain the role of

---

<sup>4</sup>BWS Case 1 and SC data are often collected at different moments of the survey design and collection process. Outcomes of the former are for example regularly used to determine which attributes from a larger pool of attributes need to be included in the SC experiment.

attributes. There is, however, not a one-to-one relationship between the different survey methods and this implies that researchers, while being keen to explore the additional insights provided by BWS data should not treat SC and BWS survey methods as equivalent and interchangeable.

The remainder of this paper is organised as follows. Section 2 explains the methodology of the joint model. The survey design and the data is described in section 3. The case study is analysed in section 4, which is followed by a conclusion section.

## 4.2 Methodology

In this section, we look at the individual components of our model framework before discussing estimation results.<sup>5</sup> For the sake of brevity, we use “BWS1” and “BWS2” to represent “BWS Case 1” and “BWS Case 2” respectively.

### 4.2.1 Model framework

As mentioned in the Introduction, our model is developed based on the assumption of correlation between SC responses and BWS1/2 responses. Latent variables are introduced to capture the correlation and to simultaneously explain different types of responses within a single ICLV framework. We follow the adoption of the notion “*attribute importance*” from [Hess and Hensher \(2013\)](#) to represent latent variables for each attribute as SC, BWS1 and BWS2 surveys all reveal people’s preferences towards various attributes in the decision-making process.<sup>6</sup>

Fig. 4.1 illustrates our joint modelling framework, where items in rectangulars are observable to researchers while items in ellipses are unobserved. The model has three components, explaining the SC responses, BWS1 responses and BWS2 responses respectively. The latter two form the measurement model components.

---

<sup>5</sup>Prior to the work of this paper, an exploratory analysis on comparing and combining SC data and BWS Case 1 data was conducted. The part of quantitative analysis is shown in Appendix B.2.

<sup>6</sup>It needs to be noted that the concept of the latent *attribute importance* in our paper is not equivalent to the “importance” defined by Marley, Flynn and Louviere (2008). In that work, the term “importance” was used to describe the “weights” of attributes in decision-making. The impact of an attribute level was assumed to be a function of the “importance” of the attribute (i.e. “weights”) and the “utility” associated with that specific level of the same attribute (i.e. “scale”). In our study, *attribute importance* reflects the underlying factor that influences the responses in different types of surveys. Essentially, we are not trying to separate “weights” and “scale” and we do not have the identifiability problem as discussed in that paper.

All three components are influenced and connected by the attribute-specific latent variable of *attribute importance*. As such, we do not impose restrictions on how an attribute (or attribute level) is evaluated between BWS1/2 data and SC data as in the work by [Balbontin et al. \(2015\)](#). We also do not directly feed the BWS1 and BWS2 responses as explanatory variables into the choice model component as [Beck et al. \(2017\)](#) did. Thereby, the proposed model has greater flexibility in recovering the correlations between BWS and SC responses, data collected through different methods can be synthesised without the risk of introducing endogeneity bias or measurement error.

More precisely, latent *attribute importance* variables are used in the “utility” functions as explanatory variables for each elicitation procedure. Herein, the “utility” concept measured in each data collection method differs. That is, “utility” in the SC component indeed means the utility derived from an alternative, but it refers to the weight attached to an attribute in the BWS1 component and the attractiveness of an attribute level in the BWS2 component. In the remainder of this paper, we use utility in quotes, i.e. “utility”, to refer to the dependent variable in each type of tasks for the sake of brevity. We assume the marginal utility of an attribute in SC component to be a function of the attribute-specific latent *attribute importance*, which also determines the same attribute’s weight in BWS1 component as well as the attractiveness of attribute levels of the same attribute in BWS2 component. Different coefficients are specified to capture the different impact of a same latent *attribute importance* in different methods.

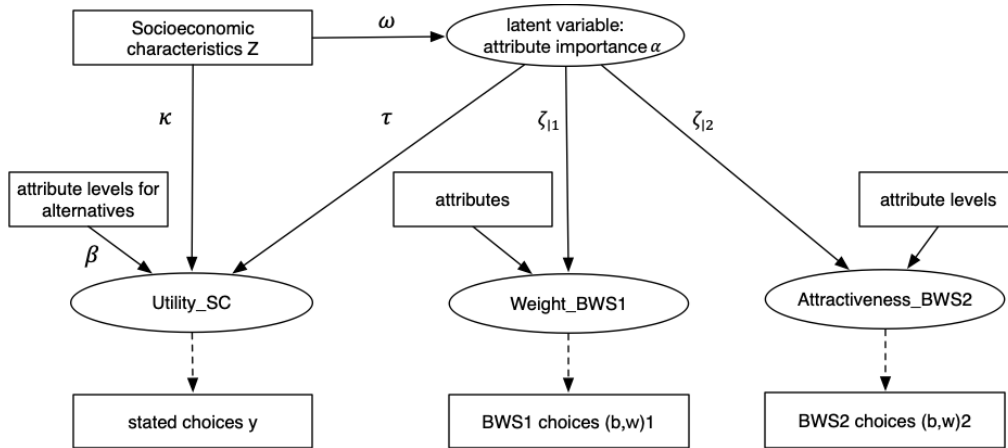


Fig. 4.1: Framework of the joint model.

## 4.2.2 Structural equations for latent variables

We denote the attribute-specific latent variables of *attribute importance*, as perceived by respondent  $n$ , by the vector  $\alpha_n = (\alpha_{n1}, \dots, \alpha_{nK})'$ , where  $K$  describes

the total number of attributes. Selected socio-demographic characteristics  $Z_n$  are used to explain the latent variables in the structural equations:

$$\alpha_{nk} = \omega'_k Z_n + \eta_{nk}, \quad (k = (1, \dots, K)), \quad (4.1)$$

where  $\eta_{nk}$  is a standard Normal error term and where the estimated vector of parameters  $\omega_k$  measures the impact of the socio-demographic characteristics on the latent variable. Note that  $Z_n$  is centred on 0, such that the latent variable  $\alpha_{nk}$  has a mean of 0.

### 4.2.3 Choice model

Let  $U_{int}$  in Eq. 4.2 represent the utility of alternative  $i$  for respondent  $n$  in stated choice task  $t$ .  $U_{int}$  consists of a deterministic portion  $V_{int}$ , and an unobserved error term  $\varepsilon_{int}$  which is independently and identically distributed (IID) extreme value type I.

$$U_{int} = V_{int} + \varepsilon_{int} = \delta_i + \beta'_n x_{int} + \varepsilon_{int}. \quad (4.2)$$

The term  $\delta_i$  is an estimated alternative-specific constant (ASC) while  $x_{int} = (x_{int1}, \dots, x_{intK})'$  is a vector of explanatory variables representing the  $K$  attributes of alternative  $i$  as shown to respondent  $n$  in SC task  $t$ , where the estimated vector  $\beta_n = (\beta_{n1}, \dots, \beta_{nK})'$  captures the marginal utilities of these attributes. Hence, it is assumed that each attribute contributes to the utility of an alternative in an additive manner, and that the marginal utility for each attribute is kept generic across alternatives.

Marginal utility varies across respondents due to the role of the latent *attribute importance*, as well as additional observed and unobserved preference heterogeneity that is independent of the latent variable. For an attribute where we assume a positive marginal utility, we specify  $\beta_{nk}$  such that:

$$\beta_{nk} = e^{\tau_k \alpha_{nk}} \cdot e^{\kappa_k Z_n} \cdot e^{\mu_{\ln \beta_k} + \sigma_{\ln \beta_k} \cdot \xi_{nk}}, \quad (4.3)$$

where, for an attribute with an expected negative marginal utility, we instead work with the negative exponential.

Latent *attribute importance* is accommodated in an exponential form to act as a positive scalar on marginal utility where  $\tau_k$  captures the degree of scaling (Hess and Hensher, 2013). To avoid overstating the role of latent *attribute importance* in explaining heterogeneity in the SC data (Vij and Walker, 2016), we let the socio-demographics  $Z_n$  which explain the latent variable  $\alpha_{nk}$  in the structural equations also directly enter the marginal utility, where the vector  $\kappa_k$  measures the direct impacts from socio-demographics  $Z_n$  on the scaling of marginal utility. Additional random heterogeneity that is not linked to the latent variable is

accommodated by specifying the underlying parameter, net of the influence of socio-demographics and the latent variable, to follow a Lognormal distribution. We then have that  $\mu_{\ln\beta_k}$  and  $\sigma_{\ln\beta_k}$  denote the mean and standard deviation of the underlying Normal distribution, where  $\xi_{nk}$  follows a standard Normal distribution across respondents for attribute  $k$ . It can be observed that as  $e^{\tau_k\alpha_{nk}}$  itself follows a Lognormal distribution,  $\beta_{nk}$  does too as it is formed by a product of Lognormals.

The probability of alternative  $s$  being chosen out of  $I$  alternatives by respondent  $n$  in SC task  $t$  is then written as:

$$P(y_{nt} = s) = \frac{e^{\delta_s + \sum_{k=1}^K \beta_{nk} x_{sntk}}}{\sum_{i=1}^I e^{\delta_i + \sum_{k=1}^K \beta_{nk} x_{intk}}}, \quad (4.4)$$

where this is dependent on a specific realisation of the vector of random coefficients.

#### 4.2.4 Measurement models

In explaining BWS1 and BWS2 data, we adopt the MaxDiff model (Marley and Louviere, 2005; Marley et al., 2008) and attempt to explain the choice for the observed pair of best and worst attributes, or attribute levels, respectively. Let  $B_{qnm|c}$  denote the ‘‘utility’’<sup>7</sup> of  $q$  for respondent  $n$  as shown in BWS task  $m$  and BWS type  $c$ , where  $c = 1$  stands for BWS1 and  $c = 2$  for BWS2. MaxDiff models explain the choice of the combination of attributes or attribute levels with the largest difference in ‘‘utility’’ between them. We thus define:

$$BW_{(q,j)nm|c} = B_{qnm|c} + W_{jnm|c} + \nu_{qjnm|c}, \quad (4.5)$$

where  $B_{qnm|c}$  and  $W_{jnm|c}$  give the ‘‘utility’’ of the two attributes or attribute levels that would be used to create the combination  $(q, j)$  while  $\nu_{qjnm|c}$  denotes a standard extreme value type I error term operating at the level of the attribute (level) pairs allowing us to operate within the MNL framework when deriving the probability of a given pair being the one with the largest difference in ‘‘utility’’. Rather than simply assuming symmetry between the ‘‘utilities’’ for the best and worst levels, we set:

$$W_{jnm|c} = -\lambda_{j|c} B_{jnm|c}, \quad (4.6)$$

thus accounting for scale difference between the ‘‘best’’ and the ‘‘worst’’ stage and allowing this difference to be attribute-specific, while still assuming that the driving factors of making an attribute (level) attractive or unattractive are the same across the two stages.

---

<sup>7</sup>As mentioned in section 4.2.1, utility in quotes, i.e. ‘‘utility’’, refers to the weight of an attribute in BWS1 tasks, and the attractiveness of an attribute level in BWS2 tasks.



#### 4.2.4.1 BWS1 data

In the BWS1 setting, we work with attributes rather than attribute levels. The “utility” function is specified to represent the weight placed on an attribute  $k$  by respondent  $n$  in task  $m$  in decision-making. Thus we have a single “utility” for a given attribute  $k$  to be “best” attribute, which is given by:<sup>8</sup>

$$B_{knm|1} = \delta_{k|1} + \zeta_{k|1}\alpha_{nk}, \quad (4.7)$$

where this is generic across BWS1 tasks as the attribute levels are not used. In Eq. 4.7, we have a constant  $\delta_{k|1}$  and a sensitivity  $\zeta_{k|1}$  with respect to the latent variable, where these two parameters are to be estimated. Since  $\alpha_{nk}$  is centred on 0,  $\delta_{k|1}$  captures the mean weight of attribute  $k$  in the BWS1 data, while  $\zeta_{k|1}$  captures the variation in the weight of the attribute in the sample due to latent attribute importance. Respondents who perceive higher importance to an attribute are expected to care more about that attribute in the BWS1 data.

#### 4.2.4.2 BWS2 data

In the BWS2 data, we work with multiple levels across attributes. The BWS2 “utility” function describes the attractiveness of an attribute level (or value)  $k$  perceived by respondent  $n$  in tasks  $m$ . The specification for a given attribute level  $k$  now depends on whether this attribute is treated as continuous or categorical. We explicitly here do not allow for scenarios in which multiple values for the same attribute are shown on one screen, i.e. only allowing for screens where each element is from a different attribute.

Let us define  $x_{knm|2}$  to be the value of continuous variable  $k$  as shown in BWS2 task  $m$  for respondent  $n$ . We then define  $B_{knm|2}$  to be equal to:

$$B_{knm|2} = \delta_{k|2} + \gamma_{k|2} \cdot e^{\zeta_{k|2}\alpha_{nk}} x_{knm|2}. \quad (4.8)$$

Here, we assume that the attractiveness of a level depends in a linear fashion on the actually presented value  $x_{knm|2}$ ,  $\delta_{k|2}$  captures the constant associated with

---

<sup>8</sup>In an ICLV model, it is common practice to use the latent variable solely to capture heterogeneity in the measurement component, and only a limited number of studies have also directly included additional randomness irrelevant from the latent variable in the measurement model. We have tried to estimate models with such direct random component in the measurement model for the BWS1 data. However, log-likelihood ratio test suggests accounting for such randomness cannot bring about significant improvement in fit or help better explain choices in our case. The interpretation of the estimation results are nevertheless quite similar to the old model, indicating that our findings on the correlation among different survey methods are relatively consistent across different model specifications. This also applies to the specification for BWS2 data in Eqs. 4.8 and 4.9.

attribute  $k$  and  $\gamma_{k|2}$  captures the baseline marginal attractiveness of the attribute level on  $B_{qnm|2}$ . This marginal attractiveness is then affected by the latent variable, where  $\zeta_{k|2}$  scales the level spacing based on latent attribute importance.

The treatment is different if attribute  $k$  is a categorical variable. In that case, a specific level will apply. Let us assume that attribute  $k$  takes  $L_k$  possible values in a survey. We would then have:

$$B_{knm|2} = \phi_{k_1|2} (x_{knm|2} == 1) + \sum_{l=2}^{L_k} \phi_{k_l|2} (e^{\zeta_{k|2}\alpha_{nk}}) (x_{knm|2} == l). \quad (4.9)$$

In this specification, we have a sum over all the possible levels that could apply for attribute  $k$ , where only one of these will apply in a given BWS2 scenario, and where the bracket  $(x_{knm|2} == l)$  will be equal to 1 for that specific level. We now estimate the baseline attractiveness of each level for the categorical attribute through  $\phi_{k_l|2}$ . The baseline attractiveness parameter  $\phi_{k_l|2}$  is then further re-scaled by the corresponding latent attribute importance through  $\zeta_{k|2}$ , where this impact of the latent variable is attribute rather than attribute-level specific. We do not scale the base level (i.e.  $l = 1$ ) to avoid the situation where an individual with higher *attribute importance* derives higher attractiveness from the base level of attribute  $k$  than other individuals. Under the current specification, respondents with higher attribute importance then exhibit a wider gap in terms of attractiveness between a higher level and the lowest (base) level for that attribute than others do.

#### 4.2.4.3 Normalisation and best-worst choice probability

For normalisation purpose, one attribute in the MaxDiff BWS1 model and one attribute level across all attributes in the MaxDiff BWS2 model need to be selected as the base by fixing the associated parameters to 0.

Due to the experimental design, the choice set varies over respondents and tasks, and this thus affects what is possible for a respondent to select as the combination of best and worst attributes or attribute levels in a given scenario. We use  $\mathbb{D}_{nm|c}$  to define the set containing all the available items presented to respondent  $n$  in BWS task  $m$  and type of BWS data  $c$ . The items in  $\mathbb{D}_{nm|c}$  allow forming the set  $\mathbb{S}_{nm|c}$  containing all the possible best-worst pairs of the available attributes or attribute levels, respectively. The best-worst choice probabilities of respondent  $n$  selecting  $h$  as the best and  $r$  as the worst ( $h, r \in \mathbb{D}_{nm|c}, r \neq h, (h, r) \in \mathbb{S}_{nm|c}$ ) in BWS task  $m$  can then be written as:

$$P\left((b, w)_{nm|c} = (h, r)\right) = \frac{e^{BW_{(h,r)nm|c}}}{\sum_{(q,j) \in \mathbb{S}_{nm|c}} (e^{BW_{(q,j)nm|c}})}, \quad (4.10)$$

making use of the appropriate combinations of Eqs. 4.5 - 4.9.

### 4.2.5 Log-likelihood

The unconditional probability of observing the sequence of stated choices  $y_n$  and best-worst responses  $(b, w)_n$  can be expressed as the integral of the multiplication of the conditional stated choice probabilities and the conditional best-worst choice probabilities over the distribution of  $\eta_n$ , the random component of the latent variables  $\alpha_n$ , and over the distribution of  $\xi_n$ , the random component of the unobserved preference heterogeneity irrelevant from  $\alpha_n$ , such that the log-likelihood is given by:

$$LL(y, (b, w)) = \sum_{n=1}^N \ln \int_{\xi_n} \int_{\eta_n} \left( \prod_{t=1}^{T_n} P(y_{nt} | \beta_n) \prod_{m|1=1}^{M_{n|1}} P((b, w)_{nm|1} | \alpha_n) \prod_{m|2=1}^{M_{n|2}} P((b, w)_{nm|2} | \alpha_n) \right) f(\eta_n) g(\xi_n) d\eta_n d\xi_n \quad (4.11)$$

where  $T_n$ ,  $M_{n|1}$  and  $M_{n|2}$  give the total numbers of the SC tasks, the BWS1 tasks, and the BWS2 tasks shown to respondent  $n$ . Meanwhile, choice observations  $y_{nt}$ ,  $(b, w)_{nm|1}$ ,  $(b, w)_{nm|2}$  refer to the chosen alternative in a SC task, the chosen best-worst pair of attributes in a BWS1 task, and the best-worst pair of attribute levels selected in a BWS2 task, respectively. Since the resulting  $LL$  does not have closed-form expression, the value of the log-likelihood needs to be approximated through simulation (Train, 2009).

### 4.2.6 Hypothesis

A hypothesis is put forward with respect to the correlations among stated choices, BWS1 responses and BWS2 responses as well as the role of latent *attribute importance* in the joint model. Providing that a higher value of the latent variable is associated with stronger *attribute importance*, we expect the signs of the impact factors of *attribute importance* in the choice model and measurement models (i.e.  $\tau, \zeta_{|1}, \zeta_{|2}$ ) to all be positive. That is, respondents who perceive higher importance from an attribute would have a higher probability to:

- be more sensitive (i.e. higher marginal utility) to the attribute in SC tasks;
- give more weight to the same attribute per se in BWS1 tasks;

- experience a wider gap in terms of attractiveness between a higher level and the lowest level (i.e. higher marginal attractiveness) for the attribute concerned in BWS2 tasks.

Of course, the same result also applies if all signs are negative, i.e. a higher latent variable leads to lower sensitivities in SC, lower weights in BWS1 and narrower attractiveness gaps in BWS2. In that case, the latent variable would be interpreted as reduced *attribute importance*. Opposite signs for the different effects or insignificance indicate a lack of consistency for the associated attribute across datasets. If fixing all the impact factors to 0, the joint ICLV model would be equivalent in specification to a model which pools all the three datasets but ignores any correlations in between. In this sense, our model can identify to what extent the choices made and the role of attributes played are consistent across different types of tasks and explore whether the behavioural information contained in BWS1 and BWS2 data could help improve the understanding of SC data.

It is worth noting that the latent variables of *attribute importance* are not used to show the influence on an attribute in comparison to other attributes, but instead to explain part of the variation across individuals. That is, if the hypothesis can be confirmed, *ceteris paribus*, a higher value of the latent attribute importance  $\alpha_{nk}$  would mean individual  $n$  is relatively more strongly influenced by attribute  $k$  in different tasks than other individuals, rather than indicating perceiving more importance from attribute  $k$  than from other attributes.

## 4.3 Case study: Survey and data

### 4.3.1 Survey background

Our research is conducted in the context of HSR (high-speed rail)-air intermodality in China. This integrated HSR-air service has been put into practice since 2011 in Shanghai with an aim to enhance the connectivity of Shanghai and its non-airport catchment area by enabling passengers to jointly travel by HSR and air on a single trip with a convenient and even seamless transfer between the two different modes and without the need of purchasing HSR and flight tickets separately.

Since collecting data from real passengers at an airport terminal is very difficult,<sup>9</sup> we tried to gain more behavioural and preference information from each

---

<sup>9</sup>A preliminary pilot survey conducted at Shanghai Hongqiao Airport where the HSR-air intermodal service was available suggested low chance of intercepting transfer passengers, low

respondent. Concerning this, we used SC, BWS1 and BWS2 tasks in the survey to understand how people react to the relatively new integrated HSR-air mode.

We collected data at Pudong International airport in Shanghai in January 2017. A total of 123 respondents answered 8 SC tasks, 7 BWS1 tasks and 8 BWS2 tasks. The SC component repeatedly asked participants to choose the most favourable alternative including the new HSR-air alternative. The BWS1 tasks examined the relative weight of all the 7 attributes involved in the SC tasks. The BWS2 tasks focused on the relative attractiveness of 14 attribute levels across 4 attributes of interest.

A detailed description of survey background, socio-demographic composition, SC experimental design, and descriptive analysis on the SC data can be found in [Song et al. \(2018\)](#). All the respondents were shown tasks in the order of SC, BWS1 and BWS2, thus any ordering effects cannot be addressed in our study. We did so to ensure that respondents would be aware of the choice scenarios and the meaning of attributes involved in the SC tasks when they responded to the BWS1 and BWS2 tasks.

#### 4.3.2 SC tasks

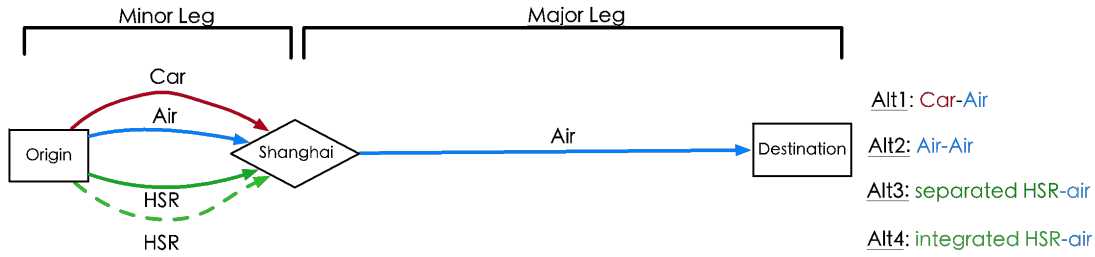
The context of the SC tasks is framed in the following way:

- a passenger is travelling from a domestic origin O to an overseas destination D;
- direct flights from O to D are unavailable;
- a passenger from O to D needs to travel via Shanghai;
- a passenger can only travel by air between Shanghai and D.

Four alternatives were shown to respondents, namely car-air, air-air, separated HSR-air and integrated HSR-air. As shown in Fig. 4.2, we denote the first leg between O and Shanghai as the “minor leg” on which various modes are available, and the second leg between Shanghai and D as the “major leg” where air is the only option. Car-air means using car on the minor leg and using flight on the major leg; air-air means taking a connecting flight; separated HSR-air refers to the traditional way of purchasing air and HSR tickets separately; integrated HSR-air refers to the new HSR-air intermodal service.

---

willingness of outbound passengers to participate in the survey, and little knowledge about HSR-air intermodality of the participants. This also explains why we instead collected data at Pudong International Airport for the formal survey as it was much easier to approach transfer passengers there.



**Fig. 4.2:** Illustration of choice scenarios in the SC survey.

The SC survey was generated through a  $D$ -efficient design (Rose and Bliemer, 2007) in Ngene (Metrics, 2012). Each respondent was presented with 8 SC tasks in a randomised order, giving a total of 984 stated choice observations. Fig. 4.3 shows an example of the SC tasks. A total of 7 attributes were incorporated, including minor time, connection time, transfer time, delay protection, ticket integration, luggage integration and travel cost. Minor time gives the time spent on the minor leg; transfer time denotes the time spent on transferring between the minor leg and the major leg;<sup>10</sup> and connection time means the time spent on waiting and going through various procedures (e.g. security check-in, luggage check-in) at the departure airport of the major leg. Travel cost gives the total expenditure for the journey, and delay protection indicates to what extent a respondent would be compensated in case of delay on the minor leg. Ticket integration and luggage integration are two attributes describing the extent of integration of the ticketing systems and luggage-handling systems between the HSR side and the air side, of which the detailed levels can be found in Table 4.2.

From the SC observations, we find that the integrated HSR-air alternative was most frequently chosen (41.57%), followed by the separated HSR-air alternative (26.42%), whereas car-air was selected for the least number of times (9.35%), which indicates relatively strong attractiveness of the integrated service and its potential market.

### 4.3.3 BWS Case 1 tasks

The BWS1 section required respondents to choose the attributes that they weighted the most and the least in each task. A balanced incomplete block design (BIBD) was adopted to generate the BWS1 experiment which could ensure each attribute occurred the same number of times and co-occurred with any other attribute the same number of times across all the choice tasks (Louviere

<sup>10</sup>Transfer time has three levels: it takes a value of 0min to indicate a seamless transfer in the same transport hub and takes the level of either 45min or 90min to suggest a transfer between two different hubs.

### 4.3. Case study: Survey and data

	Car-air	Air-air	Separated HSR-air	Integrated HSR-air
Travel cost	¥1,250	¥1,050	¥1,150	¥1,250
Minor time	5h	1.5h	2.5h	2.5h
Transfer time	0h	0h	1.5h	1.5h
Connection time	1.5h	4h	1.5h	2.5h
Delay protection	None	Free flight change	None	50% discount on changing flight
Ticket integration	-	<ul style="list-style-type: none"> <li>• Book together</li> <li>• Fixed-time flight on minor leg</li> <li>• Easy collection</li> </ul>	<ul style="list-style-type: none"> <li>• Book separately</li> <li>• Fixed-time train on minor leg</li> <li>• No easy collection</li> </ul>	<ul style="list-style-type: none"> <li>• Book together</li> <li>• Fixed-time train on minor leg</li> <li>• Easy collection</li> </ul>
Security check and luggage integration	-	<ul style="list-style-type: none"> <li>• Two security checks</li> <li>• No integrated luggage handling system</li> </ul>	<ul style="list-style-type: none"> <li>• Two security checks</li> <li>• No integrated luggage handling system</li> </ul>	<ul style="list-style-type: none"> <li>• One security check</li> <li>• Integrated luggage handling system available</li> </ul>

**Fig. 4.3:** Example of SC tasks.

et al., 2015). In our survey, 7 attributes were assigned into 7 randomly-displayed BWS1 tasks, each with 4 attributes. Consequently, each attribute was shown to each respondent 4 times and each pair of attributes occurred twice. The detailed information of experimental design is presented in Appendix B.1 and Fig. 4.4 shows an example of the BWS1 tasks.

Most	If you are going to buy an integrated HSR-air service, what factors do you consider as the most important and least important?	Least
<input type="checkbox"/>	Minor time	<input type="checkbox"/>
<input type="checkbox"/>	Delay protection	<input type="checkbox"/>
<input type="checkbox"/>	Connection time	<input type="checkbox"/>
<input type="checkbox"/>	Travel cost	<input type="checkbox"/>

**Fig. 4.4:** Example of BWS1 tasks.

An easy way to analyse BWS data is to compute the simple best-minus-worst (B-W) scores for each attribute.<sup>11</sup> Table 4.1 summarises the simple B-W score for each attribute averaged across respondents in descending order as well as the standard deviation (s.d.) of individual-level simple B-W scores for each attribute.

<sup>11</sup>Simple best-minus-worst scores can be obtained by subtracting the total count of an item being chosen as the worst from the total count the same item being chosen as the best across all BWS choice tasks and across all respondents (Louviere et al., 2015). Since each attribute appeared 4 times per person in our case, the simple B-W score averaged at the individual-level is between -4 and 4.

A higher B-W score means greater weight to the corresponding attribute in deciding whether to buy an integrated HSR-air option. These scores provide a straightforward implication that minor time and ticket integration mattered the least, whereas connection time and travel cost are the two attributes that mattered the most by the sample. The standard deviations of B-W scores suggest that respondents gave more diverse weight to the time-unrelated attributes than to time-related attributes. Minor time has the lowest B-W scores and is the attribute with the second lowest standard deviation of B-W scores, indicating that it was universally considered of limited importance. This is understandable as our survey was based in Shanghai and its nearby regions which could be reached by HSR or air from Shanghai within a relatively short period of time.

**Table 4.1:** Average simple B-W scores and standard deviation for BWS1 data

Attribute	B-W score	s.d.	Score ranking
CT (connection time)	0.37	2.00	1
TC (travel cost)	0.33	2.49	2
DP (delay protection)	0.29	2.35	3
TT (transfer time)	0.23	1.77	4
LI (luggage integration)	0.16	2.61	5
TI (ticket integration)	-0.47	2.27	6
MT (minor time)	-0.90	1.77	7

#### 4.3.4 BWS Case 2 tasks

The BWS2 section consisted of 8 tasks, each comprising the attribute levels which constituted the profile of the integrated HSR-air alternative in each SC task. That is to say, the BWS2 tasks were not obtained from a separate independent experimental design, but were “adapted” from the experimental design for the SC tasks. Our BWS2 survey focused on four attributes, i.e. connection time, delay protection, ticket integration and luggage integration, such that each BWS2 task required respondents to select the most appealing and the least appealing from 4 available attribute levels.<sup>12</sup> We did not involve the full package of attributes in the BWS2 tasks as in SC or BWS1 tasks for the sake of reducing cognitive burden and zooming in on those relatively new attributes of HSR-air. As the latent *attribute importance* is not used to show the influence of an attribute in comparison to other attributes, but to explain part of the inter-individual

<sup>12</sup>The levels were always shown in the order of connection time, delay protection, ticket integration and luggage integration to reduce cognitive burden. Comparisons between levels within a same attribute were not allowed.



### 4.3. Case study: Survey and data

preference heterogeneity, not presenting levels for the remaining three attributes would not affect the distributions or the impact of the latent *attribute importance* across individuals for the four attributes involved in the BWS2 tasks.

Fig. 4.5 gives an example of the BWS2 tasks, where different levels across different attributes were evaluated on a common scale rather than being compared within an attribute, such that a respondent might prefer “having 50% off on a flight change” over “having an integrated luggage-handling system and one security check”.

Most	Given that the integrated HSR-air service costs 1250RMB, takes 2.5h on the minor (HSR) leg, and requires a transfer between Hongqiao HSR station and Pudong airport, which of the following are the most and the least appealing?	Least
<input type="checkbox"/>	Connection time: 2.5h	<input type="checkbox"/>
<input type="checkbox"/>	50% off on changing flight	<input type="checkbox"/>
<input type="checkbox"/>	Book together, fixed-time train on the minor leg and easy collection	<input type="checkbox"/>
<input type="checkbox"/>	Integrated luggage-handling and one security check	<input type="checkbox"/>

**Fig. 4.5:** Example of BWS2 tasks.

Overall, 14 different attribute levels were included in the BWS2 survey as listed in Table 4.2, including 5 levels of connection time, 3 levels of delay protection, 3 levels of ticket integration and 3 levels of luggage integration.

It should be noted that each item was not necessarily presented to all of the 123 respondents and did not occur with a same frequency. Thus, we calculate analytical B-W scores<sup>13</sup> to show relative attractiveness of the attribute levels among the sample. As shown in Table 4.3, we can see an increase in the analytical B-W scores as the level goes up for delay protection and luggage integration. However, for ticket integration, the scores are generally low and close to each other, indicating that the three levels of ticket integration were almost equally attractive to the respondents. One interesting thing is that connection time appears to be generally considered less attractive, regardless of which actual value it takes. This is understandable as connection time was considered as the most important factor in the BWS1 tasks so that the respondents felt all the values of connection time presented in the BWS2 tasks to be unattractive.

<sup>13</sup>Analytical B-W scores can be obtained by  $\ln\left(\frac{1+\frac{N_b-N_w}{N_x}}{1-\frac{N_b-N_w}{N_x}}\right)$ , where  $N_b - N_w$  is the simple B-W score and  $N_x$  is the total times of the item being available, such that the score can rule out the impact of uneven occurrence of each attribute (Lipovetsky and Conklin, 2014; Marley et al., 2016).

**Table 4.2:** Summary of the attribute levels in BWS2 tasks

#	Attribute level	Meaning	Numbers of respondents shown	Times available	Times as the best	Times as the worst
1	conn150	Connection time is 2.5h	123	235	32	53
2	conn180	Connection time is 3h	111	172	15	83
3	conn210	Connection time in 3.5h	123	280	25	97
4	conn270	Connection time is 4.5h	74	162	2	93
5	conn330	Connection time is 5.5h	87	135	1	103
6	delay0	No delay protection	123	320	20	155
7	delay1	50% off on changing flight should missing major-leg flight due to the delay on minor leg	123	319	80	64
8	delay2	Changing flight for free should missing major-leg flight due to the delay on minor leg	123	345	131	39
9	tick1	Booking tickets together, no easy collection, fixed-time train on the minor leg	123	379	96	64
10	tick2	Booking tickets together, easy ticket collection available, fixed-time train on the minor leg	123	324	76	56
11	tick3	Booking tickets together, eash ticket collection available, flexible train on the minor leg	111	281	91	38
12	lugg0	No luggage integration, security checks required on both minor and major legs	99	138	2	67
13	lugg1	Integrated luggage-handling system available, security checks required on both minor and major legs	110	448	179	54
14	lugg2	Integrated luggage-handling system available, one security check required	123	398	234	18

#### 4.4. Case study: Model estimation

The scores are used for descriptive analysis for better understanding the BWS1 and BWS2 data. All in all, we wish to study the correlation across the different datasets. The B-W scores themselves do not allow us to do so because we can only calculate the scores for BWS1 and BWS2 data independently, regardless of the calculation method we adopt. We need the joint model to simultaneously estimate on SC, BWS1 and BWS2 data and to explore the correlations among them.

**Table 4.3:** Analytical B-W scores for BWS2 data at the sample level

Attribute level	Analytical B-W score	Score ranking
conn150	-0.18	8
conn180	-0.84	10
conn210	-0.53	9
conn270	-1.27	13
conn330	-1.97	14
delay0	-0.90	11
delay1	0.10	7
delay2	0.55	3
tick1	0.17	5
tick2	0.12	6
tick3	0.38	4
lugg0	-1.02	12
lugg1	0.57	2
lugg2	1.22	1

## 4.4 Case study: Model estimation

### 4.4.1 Model specification

The models in this paper were estimated in R using [CMC \(2017\)](#), and 1000 MLHS draws ([Hess et al., 2006](#)) were used in simulation. We used likelihood ratio test to gradually improve the model specification and select the best model fit. We also removed some insignificant variables due to the small sample size and continuously checked the impact on willingness-to-pay estimates. This section describes the final specification of the joint ICLV model we have found which produces the most sensible behavioural interpretation.

#### 4.4.1.1 Structural equations

After regressing the BWS1 individual-specific simple B-W scores of each attribute on different socio-demographic characteristics, the adopted structural equations for the 7 latent variables of attribute importance  $\alpha_{nk}$  in Eq. 4.1 are defined as:<sup>14</sup>

$$\begin{aligned}
 \alpha_{n,MT} &= \eta_{n,MT}, \quad (k = \text{Minor Time}) \\
 \alpha_{n,CT} &= \eta_{n,CT}, \quad (k = \text{Connection Time}) \\
 \alpha_{n,TT} &= \eta_{n,TT} + \omega_{TT,age>45} \cdot Z_{age>45}, \quad (k = \text{Transfer Time}) \\
 \alpha_{n,DP} &= \eta_{n,DP} + \omega_{DP,male} \cdot Z_{male}, \quad (k = \text{Delay Protection}) \\
 \alpha_{n,TI} &= \eta_{n,TI} + \omega_{TI,age>35} \cdot Z_{age>35}, \quad (k = \text{Ticket Integration}) \\
 \alpha_{n,LI} &= \eta_{n,LI} + \omega_{LI,age>45} \cdot Z_{age>45}, \quad (k = \text{Luggage Integration}) \\
 \alpha_{n,TC} &= \eta_{n,TC} + \omega_{TC,reimbursed} \cdot Z_{reimbursed}, \quad (k = \text{Travel Cost})
 \end{aligned} \tag{4.12}$$

where  $\eta_{nk}$  follows a standard Normal distribution among respondents. All socio-demographic variables used are rescaled to be centred on 0. We have not found suitable socio-demographics for the determinants of the latent attribute importance of minor time and connection time. Thus  $\alpha_{n,MT}$  and  $\alpha_{n,CT}$  are assumed to be purely random.

#### 4.4.1.2 Choice model on SC data

For normalisation purposes, the alternative-specific constant  $\delta_i$  for the integrated HSR-air alternative is fixed to 0 while the other 3 alternative-specific constants are estimated. We assume  $\tau_{MT} = 0$  to avoid over-specification since minor time acts as the base in the MaxDiff BWS1 model and was not included in the BWS2 survey.

Minor time, connection time and travel cost are treated as continuous variables. The remaining four attributes are treated as categorical variables, with the lowest level of each being the base in dummy coding. The sensitivity coefficients for these attributes in the stated choice component in Eq. 4.3 are denoted

---

<sup>14</sup>For the sake of consistency, in section 4.4, parameters on attributes are notated with subscripts of the capital initials of the attributes as shown in Table 4.1, and parameters on attribute levels are represented with subscripts of the abbreviation of the attribute levels in lower case as listed in Table 4.3.

#### 4.4. Case study: Model estimation

in detail as:

$$\begin{aligned}
\beta_{n,MT} &= -e^{\mu_{ln}(-\beta_{n,MT}) + \sigma_{MT}\xi_{n,MT}} \\
\beta_{n,CT} &= -e^{\tau_{CT}\alpha_{n,CT} \cdot e^{\mu_{ln}(-\beta_{n,CT}) + \sigma_{CT}\xi_{n,CT}}} \\
\beta_{n,tran45\&90min} &= -e^{\tau_{TT}\alpha_{n,TT} \cdot e^{\kappa_{TT,age>45}Z_{age>45}} \cdot e^{\mu_{ln}(-\beta_{n,tran45\&90min}) + \sigma_{TT}\xi_{n,TT}}} \\
\beta_{n,delay1\&2} &= e^{\tau_{DP}\alpha_{n,DP} \cdot e^{\kappa_{DP,male}Z_{male}} \cdot e^{\mu_{ln}(\beta_{n,delay1\&2}) + \sigma_{DP}\xi_{n,DP}}} \\
\beta_{n,lugg1\&2} &= e^{\tau_{LI}\alpha_{n,LI} \cdot e^{\kappa_{LI,age>45}Z_{age>45}} \cdot e^{\mu_{ln}(\beta_{n,lugg1\&2}) + \sigma_{LI}\xi_{n,LI}}} \\
\beta_{n,TC} &= -e^{\tau_{TC}\alpha_{n,TC} \cdot e^{\kappa_{TC,reimbursed}Z_{reimbursed}} \cdot e^{\mu_{ln}(-\beta_{n,TC}) + \sigma_{TC}\xi_{n,TC}}}
\end{aligned} \tag{4.13}$$

such that  $\beta_{n,MT}$ ,  $\beta_{n,CT}$  and  $\beta_{n,TC}$  measure the marginal utilities, while  $\beta_{n,tran45\&90min}$ ,  $\beta_{n,delay1\&2}$ , and  $\beta_{n,lugg1\&2}$  give the relative utility against the corresponding base levels, which are  $tran0min$ ,  $delay0$ , and  $lugg0$  in respective. The higher two levels for each are merged for estimation in our final specification as they are found not significantly different from each other. The final specification excludes the attribute of ticket integration from the utility function for the SC data, as it is found to contribute little to the utility functions. However, ticket integration is still used in the measurement models. Finally, parameters of  $\kappa_{DP,male}$ ,  $\kappa_{TC,reimbursed}$  and  $\tau_{DP}$  are set to zero in the final specification as they were insignificant. Besides, although we have found suitable socio to explain transfer time (i.e.  $Z_{age>45}$ ), the model with the indirect impact of  $Z_{age>45}$  becomes insignificant once the direct impact is added. Hence, in the final specification, we drop the indirect impact by fixing  $\omega_{TT,age>45} = 0$  and keep the direct impact of age on transfer time by estimating  $\kappa_{TT,age>45}$ .

##### 4.4.1.3 MaxDiff models on BWS1 data and BWS2 data

For the BWS1 data, all the 7 attributes shown in the SC survey are examined, i.e. minor time, connection time, transfer time, delay protection, ticket integration, luggage integration and travel cost. Minor time acts as the base, with relevant parameters  $\delta_{MT|1}$  and  $\zeta_{MT|1}$  normalised to 0. For the BWS2 data, connection time, delay protection, ticket integration and luggage integration are the four attributes of interest. Connection time is treated as a continuous variable and  $x_{CT,nm|2}$  can take the value of 150min, 180min, 210min, 270min or 330min. The remaining three attributes are regarded as categorical variables, with level  $delay0$ ,  $tick1$  and  $lugg0$  being the lowest (base) levels for delay protection, ticket integration and luggage integration in respective. The attribute level  $delay0$  is selected as the base in the MaxDiff BWS2 model, with the baseline attractiveness  $\phi_{delay0|2}$  fixed to 0 for normalisation.

## 4.4.2 Estimation results

For comparison, we estimated the corresponding reduced form mixed multinomial logit (MMNL) model on the SC data alone, i.e. setting  $\tau = 0, \forall k$  (Vij and Walker, 2016). The estimates of the MMNL model are shown alongside the estimates of the choice model component of the joint ICLV model in Table 4.4. In both models, the travel cost variable was scaled by 6.9, such that the value-of-time is expressed in the \$/min<sup>15</sup>.

The log-likelihood of the choice model component on the SC data of the ICLV model ( $LL(SC) = -1060.453$ ) is slightly inferior to that of the MMNL model ( $LL = -1057.396$ ), which is consistent with the discussions by Vij and Walker (2016). Indeed, the ICLV model needs to explain not only the SC data but also the extra BWS1 and BWS2 data, and it is then impossible for the ICLV model to outperform the reduced form MMNL model. Notwithstanding this, our joint ICLV model appears to provide more behavioural explanations than the reduced form MMNL model does. The  $\tau$  estimates suggest significant roles of the latent variables of *attribute importance* in scaling sensitivities for all the non-cost attributes where applicable.

The MMNL model and the ICLV model show similar preference patterns towards attributes. As shown in the upper part of Table 4.4, the most negative  $\delta_{ca}$  implies that the car-air alternative is the least preferred option, all else being equal, whereas the air-air alternative ( $\delta_{aa}$ ) and the separated HSR-air alternative ( $\delta_{sha}$ ) are both slightly less preferred compared to the base alternative, i.e. the integrated HSR-air mode. Since Lognormal distributions are used, the more negative the underlying mean parameter  $\mu_{\ln|\beta_k|}$  is, the smaller in magnitude the median of marginal utility is, which translates into a lower sensitivity to that attribute in the SC tasks. As to the standard deviations  $\sigma_{\ln|\beta_k|}$ , both models detect statistically significant random heterogeneity in sensitivities to all of the attributes. Regarding the direct impacts of socio-demographics in the utility functions, we can see from both models that  $\kappa_{TT,age>45}$  is significant at the 95% confidence interval, suggesting that older respondents are more sensitive to transfer time and dislike long transfer time more than young people do. Meanwhile, although  $\kappa_{LI,age>45}$  in the MMNL model is only significant at the 80% confidence interval, we can still infer from  $\kappa_{LI,age>45}$  in the ICLV model, which is significant at the 95% confidence interval, that older passengers can derive higher utility from better luggage integration than young people do.

In the left part of Table 4.5, the constant  $\delta_{|1}$  represents the mean of the weight to the associated attribute among the sample in the BWS1 data. It

---

<sup>15</sup>USD/CNY $\approx$  6.9 during the period of data collection.

4.4. Case study: Model estimation

**Table 4.4:** Estimates for the reduced form MMNL model and the choice model component of the ICLV model

	MMNL		ICLV	
parameter #	17		65	
individual #	123		123	
observation #	984		984	
$LL(0)$	-1364.114		whole model: -5948.766	
$LL(\text{final})$	-1057.396		SC component: -1060.453	
adj. $\rho^2$	0.2124		whole model: -4445.399	
$AIC$	2148.79		whole model: 9020.8	
$BIC$	2249.9		whole model: 9407.4	
	<b>est.</b>	<b><math>t</math>-rat.(0)</b>	<b>est.</b>	<b><math>t</math>-rat.(0)</b>
$\delta_{ca}$	-3.210	-7.49	-3.081	-6.91
$\delta_{aa}$	-0.411	-1.73	-0.439	-2.04
$\delta_{sha}$	-0.622	-3.30	-0.738	-3.60
$\mu_{\ln(-\beta_{MT})}$	-5.243	-16.51	-5.441	-14.26
$\mu_{\ln(-\beta_{CT})}$	-4.527	-37.69	-4.596	-38.62
$\mu_{\ln(-\beta_{tran45\&90min})}$	-0.900	-2.44	-1.009	-1.85
$\mu_{\ln(\beta_{delay1\&2})}$	-1.342	-2.29	-2.157	-2.42
$\mu_{\ln(\beta_{lugg1\&2})}$	-0.729	-2.32	-1.096	-2.10
$\mu_{\ln(-\beta_{TC})}$	-4.181	-22.02	-4.265	-14.51
$\sigma_{\ln(-\beta_{MT})}$	-0.558	-4.02	-0.881	-3.62
$\sigma_{\ln(-\beta_{CT})}$	-0.517	-6.11	-0.409	-5.02
$\sigma_{\ln(-\beta_{TT})}$	1.327	5.01	1.028	4.08
$\sigma_{\ln(\beta_{DP})}$	-1.203	-2.12	-1.818	-3.71
$\sigma_{\ln(\beta_{LI})}$	-1.331	-6.35	-1.246	-5.25
$\sigma_{\ln(-\beta_{TC})}$	-0.622	-3.75	-0.486	-2.81
$\kappa_{TT,age>45}$	1.669	3.73	1.468	2.54
$\kappa_{DP,male}$	0.000	-	0.000	-
$\kappa_{LI,age>45}$	0.947	1.57	1.252	2.18
$\kappa_{TC,reimbursed}$	0.000	-	0.000	-
$\tau_{CT}$			0.233	2.37
$\tau_{TT}$			0.335	2.59
$\tau_{DP}$			0.000	-
$\tau_{LI}$			0.701	4.49
$\tau_{TC}$			0.334	1.21

could be noticed that, with minor time normalised to 0, connection time, delay protection and transfer time are positioned at the higher end of the underlying weighting scale, followed by travel cost and luggage integration. Regarding the scalars in the worst choice stage shown in the lower left of Table 4.5,  $\lambda_{CT|1}$  ( $t\text{-rat}(1)=-4.27$ ) is the only one which is significantly different from 1, suggesting that scaling difference between the worst choice stage and the best choice stage only exists for the attribute of connection time. Since  $\lambda_{CT|1}$  is much lower than 1, it suggests that the model has less noise in explaining the choices in the best choice stage than in the worst choice stage for the attribute of connection time.

**Table 4.5:** Estimates of the MaxDiff measurement models on the BWS1 and BWS2 data

MaxDiff BWS1				MaxDiff BWS2			
	est.	$t\text{-rat.}(0)$	$t\text{-rat.}(1)$		est.	$t\text{-rat.}(0)$	$t\text{-rat.}(1)$
$\delta_{MT 1}$	0 (base)	-	-	$\delta_{CT 2}$	4.151	4.06	-
$\delta_{CT 1}$	1.271	5.23	-	$\gamma_{CT 2}$	-0.015	-3.86	-
$\delta_{TT 1}$	0.920	4.22	-	$\phi_{delay0 2}$	0 (base)	-	-
$\delta_{DP 1}$	1.071	3.21	-	$\phi_{delay1 2}$	2.008	5.54	-
$\delta_{TI 1}$	0.311	1.29	-	$\phi_{delay2 2}$	2.601	6.25	-
$\delta_{LI 1}$	0.738	2.37	-	$\phi_{tick1 2}$	1.956	4.86	-
$\delta_{TC 1}$	0.899	3.44	-	$\phi_{tick2 2}$	2.201	5.34	-
				$\phi_{tick3 2}$	2.536	5.93	-
				$\phi_{lugg0 2}$	-0.102	-0.33	-
				$\phi_{lugg1 2}$	2.437	5.75	-
				$\phi_{lugg2 2}$	3.432	7.60	-
$\lambda_{MT 1}$	-	-	-	$\lambda_{MT 2}$	-	-	-
$\lambda_{CT 1}$	0.255	-	-4.27	$\lambda_{CT 2}$	0.992	4.11	-0.03
$\lambda_{TT 1}$	0.600	-	-1.17	$\lambda_{TT 2}$	-	-	-
$\lambda_{DP 1}$	0.751	-	-0.98	$\lambda_{DP 2}$	0.815	7.18	-1.63
$\lambda_{TI 1}$	1.171	-	0.48	$\lambda_{TI 2}$	0.691	5.41	-2.42
$\lambda_{LI 1}$	1.018	-	0.06	$\lambda_{LI 2}$	0.755	6.59	-2.13
$\lambda_{TC 1}$	1.411	-	0.95	$\lambda_{TC 2}$	-	-	-

The right part of Table 4.5 shows estimates for the baseline attractiveness of each attribute level in the BWS2 data. Focusing on  $\phi_{|2}$ , it can be inferred that compared to ticket integration, delay protection and luggage integration are associated with overall larger steps in attractiveness when moving from a poorer level to a better level, which implies that respondents might be indifferent to variations in ticket integration. This is in line with the discoveries in the SC data and the BWS1 data as well as the preliminary findings in the normalised B-W scores in the BWS2 data. As to the attribute-specific scalars shown in the lower right of Table 4.5, only ticket integration  $\lambda_{TI|2}$  ( $t\text{-rat}(1)=-2.42$ ) and luggage integration  $\lambda_{LI|2}$  ( $t\text{-rat}(1)=-2.13$ ) are significantly different from 1. Being smaller



#### 4.4. Case study: Model estimation

than 1,  $\lambda_{TI|2}$  and  $\lambda_{LI|2}$  suggest stronger random error in the worst choice stage for these two attributes than in the best choice stage.

Now we turn to Table 4.6 to jointly examine all the impact factors of latent attribute importance in the choice model (i.e.  $\tau$ ) as well as in the two MaxDiff measurement models (i.e.  $\zeta_{|1}$  and  $\zeta_{|2}$ ). The estimation results confirm our hypothesis. Except for  $\tau_{TC}$ , all the impact factors in the choice model and the measurement models are positive and significant where applicable. Thus, choices are made in a consistent way across different types of surveys. An increase in the latent variable would result in a stronger sensitivity to the associated attribute in the SC data, an increased probability that the attribute of interest is positioned to the higher end on the weighing scale in the BWS1 data, and a wider attractiveness gap between levels of the concerned attribute in the BWS2 data.

An exception arises for travel cost, where  $\tau_{TC}$  is insignificant (est=0.334, t-rat(0)=1.21), whereas the same latent attribute importance plays a strong and significant role in BWS1 tasks (est=2.210, t-rat(0)=5.66). It is also worth noting that delay protection is related to cost as well, and that positive and significant impact of the corresponding latent attribute importance is found in both the BWS1 and BWS2 data, but not in the SC data, i.e. as mentioned earlier,  $\tau_{DP}$  is fixed to 0 in this final specification as little influence from the latent attribute importance could be found on scaling the sensitivity to delay protection in the SC data. This implies a lack of consistency for the attributes related to cost between SC and BWS1/2 data, which is in accordance with and complements the findings in [Balbontin et al. \(2015\)](#), where the sensitivity of an attribute related to cost, i.e. rent, was estimated to be inconsistent between the SC and BWS2 data. It might be due to the fact that choices in the SC experiment were made based on detailed choice contexts and level values of different attributes of each alternative in multi-alternative settings, while this information was not available in the BWS1 experiment where respondents' awareness and past experience of each attribute would influence their evaluation of the attributes ([Louviere and Islam, 2008](#); [Mueller et al., 2010](#)). In this context, compared to the other non-cost attributes, it might be more difficult to assess the importance of the cost-relevant attributes and to trade off between cost and the other non-cost attributes without knowing the actual levels for all the available options in the choice set. Consequently, the role of the latent *attribute importance* is not significant in explaining the preference variations for cost-related attributes across individuals in the SC data, but is more prominent in the BWS1/2 data.

Combining the estimates  $\omega$  in the structural equations and the impact factors for latent attribute importance, the positive  $\omega_{TI,age>35}$  and  $\omega_{LI,age>45}$  and the

**Table 4.6:** Estimates in the structural equations and impact factors of latent attribute importance in the choice model and the BWS1/2 MaxDiff measurement models

Structural equations	SC data		BWS1 data		BWS2 data						
	est	t-rat(0)	est	t-rat(0)	est	t-rat(0)					
$\omega_{MT}$	-	-	$\tau_{MT}$	-	$\zeta_{MT 1}$	0 (base)	-	$\zeta_{MT 2}$	-	-	
$\omega_{CT}$	-	-	$\tau_{CT}$	0.233	2.37	$\zeta_{CT 1}$	0.659	2.03	$\zeta_{CT 2}$	0.373	9.37
$\omega_{TT,age>45}$	0.000	-	$\tau_{TT}$	0.335	2.59	$\zeta_{TT 1}$	1.211	4.50	$\zeta_{TT 2}$	-	-
$\omega_{DP,male}$	-0.863	-2.71	$\tau_{DP}$	0.000	-	$\zeta_{DP 1}$	2.067	3.40	$\zeta_{DP 2}$	0.519	3.25
$\omega_{TI,age>35}$	0.868	3.97	$\tau_{TI}$	-	-	$\zeta_{TI 1}$	1.683	4.34	$\zeta_{TI 2}$	0.371	3.94
$\omega_{LI,age>45}$	1.191	2.66	$\tau_{LI}$	0.701	4.49	$\zeta_{LI 1}$	2.160	5.29	$\zeta_{LI 2}$	0.530	4.80
$\omega_{TC,reimbursed}$	-0.625	-3.36	$\tau_{TC}$	0.334	1.21	$\zeta_{TC 1}$	2.210	5.66	$\zeta_{TC 2}$	-	-

negative  $\omega_{TC,reimbursed}$  show that older people think ticket integration and luggage integration to be of greater importance than young people do, while passengers who get reimbursed perceive lower importance for travel cost than those who need to pay for the travel on their own. The negative and significant  $\omega_{DP,male}$  suggests that male passengers find delay protection less important than female passengers do. Parameter  $\omega_{TT,age>45}$  are fixed to 0 and not estimated in the final specification because of its very low significance. We can further look back into Table 4.4, where  $\kappa_{TT,age>45}$  and  $\kappa_{LI,age>45}$  are the only two statistically significant  $\kappa$  parameters. We can, therefore, deduce that respondents' age mainly plays an independently direct role in scaling the marginal utility of transfer time, whereas age affects the marginal utility of luggage integration both directly and indirectly via the latent variable. The remaining socio-demographic characteristics involved in  $\omega$  influence stated choice behaviour mainly through the latent variables of attribute importance.

Finally, we shed some light on willingness-to-pay (WTP) in the SC data with and without the additional information gained from the BWS1 and BWS2 data in Table 4.7. We first calculated the distributions of marginal utilities for all the attributes, taking into account of the roles of latent attribute importance and socio-demographic characteristics in the ICLV model and the role of socio-demographic characteristics in the reduced form MMNL model, i.e. marginal utilities  $\beta_{nk}$  are given by  $e^{\tau_k \alpha_{nk}} e^{\kappa_k Z_n} \beta_{nk}^*$  in the ICLV model and by  $e^{\kappa_k Z_n} \beta_{nk}^*$  in the MMNL model, where  $\beta_{nk}^* = e^{\mu_{\ln \beta_k} + \sigma_{\ln \beta_k} \cdot \xi_{nk}}$ . We then calculated the ratio against the marginal utility of travel cost for each of the remaining attributes for each draw, which is taken from the distributions of marginal utilities used in the estimation procedure, enabling us to obtain the WTP distributions for all the attributes except for travel cost through simulation (Daly et al., 2012; Hensher and Greene, 2003; Sillano and de Dios Ortúzar, 2005).

**Table 4.7:** WTP estimates of the joint ICLV model and the reduced form MMNL model.

models	attributes	sensitivities $\beta$		mean and percentiles of WTP distribution				WTP changes against MMNL			
		mean	s.d.	mean	s.d.	median	interquartile range	mean	s.d.	median	interquartile range
ICLV	Minor Time	-0.006	0.007	0.54	0.78	0.31	0.48	10%	59%	-11%	17%
	Connection Time	-0.011	0.006	0.96	0.85	0.72	0.77	-2%	-9%	1%	-5%
	Transfer Time_45&90min	-0.738	1.429	62.72	146.51	25.47	50.34	-32%	-55%	-2%	-22%
	Delay Protection_lv1&2	0.606	2.981	52.62	359.14	8.18	27.75	23%	252%	-52%	-23%
	Luggage Integration_lv1&2	1.231	5.119	104.63	509.18	23.01	62.19	8%	78%	-27%	-17%
	Travel Cost	-0.017	0.011	-	-	-	-	-	-	-	-
MMNL	Minor Time	-0.006	0.004	0.49	0.49	0.35	0.41	-	-	-	-
	Connection Time	-0.012	0.007	0.98	0.93	0.71	0.81	-	-	-	-
	Transfer Time_45&90min	-1.160	3.581	91.80	328.10	26.08	64.19	-	-	-	-
	Delay Protection_lv1&2	0.539	0.975	42.87	101.98	16.99	35.81	-	-	-	-
	Luggage Integration_lv1&2	1.221	2.833	97.05	285.32	31.44	75.02	-	-	-	-
	Travel Cost	-0.019	0.013	-	-	-	-	-	-	-	-

We see some differences between the two models here, where we would argue that the ICLV findings are more realistic especially for transfer time. Indeed, in the ICLV model, going from a transfer time of 45 or 90 minutes to a seamless transfer has the same benefit as a reduction in connection time by 81.6 minutes at the mean. In the MMNL model, this would be 122.58 minutes, which seems unrealistic if we assume that transfer time should at best be as important as connection time. In addition, the standard deviations of the three categorical attributes, i.e. transfer time, delay protection, and luggage integration are relatively large in both models. This can be mainly attributed to the long tails of the Lognormal distributed WTP distributions as the marginal utilities for all the attributes follow Lognormal distributions. Hence, apart from regular statistics of mean and standard deviation, we also show the median and interquartile range of each WTP distribution. We can see an overall reduction in the median values, and a decrease in the interquartile range for all the attributes except for minor time when we move from the MMNL model to the ICLV model. This means that the spread of the distribution is smaller and the values are more squeezed to the median for the ICLV model.

## 4.5 Conclusions

This research is conducted in the context of the introduction of a new travel mode, i.e. HSR-air intermodality. The need for better understanding of the role of attributes (especially the new ones) in the new context entails collecting more behavioural information from each individual. Compared with adopting a longer SC survey, synthesising data from multiple types of preference elicitation approaches can avoid extra cognitive burden caused by additional SC tasks and provide more robust explanation of the role that attributes play. The growing interest in BWS data has presented the potential of such data synthesis. Specifically, SC data allows us to analyse how respondents trade off between attributes and forecast demand, whereas BWS1 and BWS2 data helps in providing more behavioural insights about the role that attributes play. It needs to be noted that it is not the objective of this research to conclude which type of preference elicitation method is more correct.

Informed by the work of [Hess and Hensher \(2013\)](#), we adopt the notion of *attribute importance* and treat it as a latent variable, which acts as the connection amongst all the three types of data. The attribute-specific latent variable scales the marginal utility of the associated attribute in the choice model on the SC data. Meanwhile, it explains the weight of the attribute and scales the marginal

attractiveness of attribute levels in the measurement models on the BWS1 data and the BWS2 data respectively.

This research has for the first time collected SC data together with more than one type of BWS data from the same respondents. Our work can provide researchers with practical guidance on applying BWS1 and (or) BWS2 approaches in travel behaviour contexts, and insights of choice behaviour in different types of surveys. By simultaneously estimating on the SC, BWS1 and BWS2 data through the latent constructs of *attribute importance* in the ICLV model, we are able to examine the correlations of choice behaviour among these three different types of tasks at the individual level, which was not addressed in [Balbontin et al. \(2015\)](#), without inducing the risk of endogeneity bias or measurement error which arose in [Beck et al. \(2017\)](#). The use of BWS1 and BWS2 data in the measurement models of the ICLV model also provides richer behavioural information than the earlier work by [Hess and Hensher \(2013\)](#), where stated attribute attendance and attribute rankings were used.

Overall, our joint model shows that attribute importance can link the SC, BWS1 and BWS2 data, indicating the benefit of improving behavioural explanation by combining the BWS data with SC data. We found a high level of consistency with respect to the impact of the underlying perceived *attribute importance* on decision-making in different tasks is significantly demonstrated. The estimation results imply that an increase in attribute importance results in a stronger sensitivity to that attribute in the SC tasks, more overall weight to that attribute in the BWS1 tasks, and also wider attractiveness gaps between levels for that attribute in the BWS2 tasks. This is particularly true for non-cost attributes, including connection time, transfer time and luggage integration in our case. We have not found similar consistency for cost-relevant attributes, i.e. delay protection and travel cost, as the corresponding latent variables only impose significant impacts in the BWS1/2 data but not in the SC data. Nevertheless, we have not discovered a one-to-one relationship between different survey methods. As such, there remain some differences in how attribute importance is evaluated between SC, BWS1 and BWS2 data. We therefore think treating different survey methods as equivalent and interchangeable - for example, using BWS1 method to determine which attributes to include in SC survey - can be risky.

The lack of one-to-one consistency between different types of data is understandable as SC tasks were conducted in multi-alternative settings. Meanwhile, the detailed information of attribute levels and (or) the information of other competing alternatives were not available in BWS1 tasks, and the competing

alternatives were also not shown to respondents. Thus respondents would be more capable to make trade-offs among attributes based on the presented information in SC tasks, whereas their perceived importance of a given attribute in a BWS1/2 survey is more affected by personal experience etc. (Louviere and Islam, 2008; Mueller et al., 2010).

The finding that there is not a one-to-one relationship between the different types of data can also be due to the fact that selecting the best is different from selecting the worst, i.e. best choices are made under positive frames whereas worst choices are made within negative frames (Giergiczny et al., 2017; Rose, 2014). Given these results, we suggest that researchers should not see BWS data as a replacement for SC data in preference elicitation research. It is of course feasible to use BWS tasks alongside SC tasks for better explanation of choices made in SC tasks, and this may be especially beneficial if the number of respondents is low. We acknowledge that Hawkins et al. (2018) suggested that the conclusion of best choices and worst choice being made in different ways in many studies were due to the inadequate data. They argued that respondents made best choices and worst choices in a same way (i.e. same utility parameters), while worst choices were usually associated with greater variance in the error term (i.e. scale heterogeneity existed between best choice stage and worst choice stage). In our paper, the best choice stage and worst choice stage share the same specification but with attribute-specific scale parameters imposed on the worst stage. This means that our model is more generic and flexible, enabling us to detect whether and which attribute has different scales between best and worst stages. The results suggested that only a subset of attributes influence decision-making differently on the worst stage in comparison to the best stage. Besides, we were examining on a small sample of data, which in turn makes it difficult to adopt more complexed model specification or to validate the conclusion raised by Hawkins et al. (2018). Regarding this, it is necessary and beneficial to replicate different methods in more research contexts.

The present work also has some limitations. Firstly, systematic order effects were not accounted for in our case study as respondents were all presented with choice tasks in the order of SC, BWS1 and BWS2. Secondly, due to the restriction of sample size, all the preference variations in the BWS1 and BWS2 tasks were attributed to latent attribute importance, and we did not incorporate random heterogeneity irrelevant to latent variables in our final specification. It would be worth applying our method on other larger joint datasets with more complicated specification of random heterogeneity, while at the same time achieving a balance with a higher computational burden. Furthermore, we could test the

non-linearity in sensitivity parameters on the utility functions for alternatives in the SC data.

## **Acknowledgements**

Fangqing Song acknowledges the support of the China Scholarship Council while Stephane Hess was supported by the European Research Council through the consolidator grant 615596-DECISIONS.

## References

- Auger, P., Devinney, T. M., Louviere, J. J., 2007. Using best–worst scaling methodology to investigate consumer ethical beliefs across countries. *Journal of Business Ethics* 70 (3), 299–326.
- Balbontin, C., Ortúzar, J. d. D., Swait, J., 2015. A joint best–worst scaling and stated choice model considering observed and unobserved heterogeneity: An application to residential location choice. *Journal of choice modelling* 16, 1–14.
- Beck, M. J., Rose, J. M., 2016. The best of times and the worst of times: A new best–worst measure of attitudes toward public transport experiences. *Transportation Research Part A: Policy and Practice* 86, 108–123.
- Beck, M. J., Rose, J. M., Greaves, S. P., 2017. I can't believe your attitude: a joint estimation of best worst attitudes and electric vehicle choice. *Transportation* 44 (4), 753–772.
- Ben-Akiva, M., Walker, J., Bernardino, A. T., Gopinath, D. A., Morikawa, T., Polydoropoulou, A., 2002. Integration of choice and latent variable models. *Perpetual motion: Travel behaviour research opportunities and application challenges*, 431–470.
- Bradley, M., Daly, A., 1994. Use of the logit scaling approach to test for rank-order and fatigue effects in stated preference data. *Transportation* 21 (2), 167–184.
- Campbell, D., Hensher, D. A., Scarpa, R., 2011. Non-attendance to attributes in environmental choice analysis: a latent class specification. *Journal of environmental planning and management* 54 (8), 1061–1076.
- Carlsson, F., 2003. The demand for intercity public transport: the case of business passengers. *Applied Economics* 35 (1), 41–50.
- CMC, 2017. Cmc choice modelling code for r. [www.cmc.leeds.ac.uk](http://www.cmc.leeds.ac.uk).
- Coast, J., Flynn, T. N., Salisbury, C., Louviere, J., Peters, T. J., 2006. Maximising responses to discrete choice experiments. *Applied health economics and health policy* 5 (4), 249–260.
- Daly, A., Hess, S., Train, K., 2012. Assuring finite moments for willingness to pay in random coefficient models. *Transportation* 39 (1), 19–31.



- Dumont, J., Giergiczny, M., Hess, S., 2015. Individual level models vs. sample level models: contrasts and mutual benefits. *Transportmetrica A: Transport Science* 11 (6), 465–483.
- Dyachenko, T., Reczek, R. W., Allenby, G. M., 2014. Models of sequential evaluation in best-worst choice tasks. *Marketing Science* 33 (6), 828–848.
- Finn, A., Louviere, J. J., 1992. Determining the appropriate response to evidence of public concern: the case of food safety. *Journal of Public Policy & Marketing*, 12–25.
- Giergiczny, M., Dekker, T., Hess, S., Chintakayala, P., 2017. Testing the stability of utility parameters in repeated best, repeated best-worst and one-off best-worst studies. *European Journal of Transport and Infrastructure Research* 17 (4), 457–476.
- Hawkins, G. E., Islam, T., Marley, A., 2018. Like it or not, you are using one value representation. *Decision*.
- Hensher, D. A., 2006. How do respondents process stated choice experiments? attribute consideration under varying information load. *Journal of applied econometrics* 21 (6), 861–878.
- Hensher, D. A., Greene, W. H., 2003. The mixed logit model: the state of practice. *Transportation* 30 (2), 133–176.
- Hensher, D. A., Mulley, C., Rose, J. M., 2015. Understanding the relationship between voting preferences for public transport and perceptions and preferences for bus rapid transit versus light rail. *Journal of Transport Economics and Policy (JTEP)* 49 (2), 236–260.
- Hensher, D. A., Rose, J., Greene, W. H., 2005. The implications on willingness to pay of respondents ignoring specific attributes. *Transportation* 32 (3), 203–222.
- Hensher, D. A., Rose, J. M., 2009. Simplifying choice through attribute preservation or non-attendance: implications for willingness to pay. *Transportation Research Part E: Logistics and Transportation Review* 45 (4), 583–590.
- Hess, S., Hensher, D. A., 2010. Using conditioning on observed choices to retrieve individual-specific attribute processing strategies. *Transportation Research Part B: Methodological* 44 (6), 781–790.
- Hess, S., Hensher, D. A., 2013. Making use of respondent reported processing information to understand attribute importance: a latent variable scaling approach. *Transportation* 40 (2), 397–412.

## References

- Hess, S., Stathopoulos, A., Campbell, D., O'Neill, V., Caussade, S., 2013. It's not that i don't care, i just don't care very much: confounding between attribute non-attendance and taste heterogeneity. *Transportation* 40 (3), 583–607.
- Hess, S., Train, K. E., Polak, J. W., 2006. On the use of a modified latin hypercube sampling (mlhs) method in the estimation of a mixed logit model for vehicle choice. *Transportation Research Part B: Methodological* 40 (2), 147–163.
- Lipovetsky, S., Conklin, M., 2014. Best-worst scaling in analytical closed-form solution. *Journal of choice modelling* 10, 60–68.
- Louviere, J. J., Flynn, T. N., Marley, A. A., 2015. *Best-worst scaling: Theory, methods and applications*. Cambridge University Press.
- Louviere, J. J., Islam, T., 2008. A comparison of importance weights and willingness-to-pay measures derived from choice-based conjoint, constant sum scales and best–worst scaling. *Journal of Business Research* 61 (9), 903–911.
- Marley, A., Islam, T., Hawkins, G., 2016. A formal and empirical comparison of two score measures for best–worst scaling. *Journal of choice modelling* 21, 15–24.
- Marley, A. A., Louviere, J. J., 2005. Some probabilistic models of best, worst, and best–worst choices. *Journal of Mathematical Psychology* 49 (6), 464–480.
- Marley, A. A. J., Flynn, T. N., Louviere, J. J., 2008. Probabilistic models of set-dependent and attribute-level best–worst choice. *Journal of Mathematical Psychology* 52 (5), 281–296.
- Marti, J., 2012. A best–worst scaling survey of adolescents' level of concern for health and non-health consequences of smoking. *Social Science & Medicine* 75 (1), 87–97.
- Metrics, C., 2012. *Ngene 1.1. 1 user manual & reference guide*. Sydney, Australia: ChoiceMetrics.
- Mueller, S., Lockshin, L., Louviere, J. J., 2010. What you see may not be what you get: Asking consumers what matters may not reflect what they choose. *Marketing Letters* 21 (4), 335–350.
- Petrolia, D. R., Interis, M. G., Hwang, J., 2018. Single-choice, repeated-choice, and best-worst scaling elicitation formats: Do results differ and by how much? *Environmental and Resource Economics* 69 (2), 365–393.

## References

- Potoglou, D., Burge, P., Flynn, T., Netten, A., Malley, J., Forder, J., Brazier, J. E., 2011. Best–worst scaling vs. discrete choice experiments: an empirical comparison using social care data. *Social science & medicine* 72 (10), 1717–1727.
- Pullman, M. E., Dodson, K. J., Moore, W. L., 1999. A comparison of conjoint methods when there are many attributes. *Marketing Letters* 10 (2), 125–138.
- Rose, J. M., 2014. Interpreting discrete choice models based on best-worst data: a matter of framing. Tech. rep.
- Rose, J. M., Bliemer, M. C., 2007. Stated preference experimental design strategies. In: *Handbook of Transport Modelling: 2nd Edition*. Emerald Group Publishing Limited, pp. 151–180.
- Sillano, M., de Dios Ortúzar, J., 2005. Willingness-to-pay estimation with mixed logit models: some new evidence. *Environment and Planning A* 37 (3), 525–550.
- Song, F., Hess, S., Dekker, T., 2018. Accounting for the impact of variety-seeking: Theory and application to hsr-air intermodality in china. *Journal of Air Transport Management* 69, 99–111.
- Train, K. E., 2009. *Discrete choice methods with simulation*. Cambridge university press.
- Vij, A., Walker, J. L., 2016. How, when and why integrated choice and latent variable models are latently useful. *Transportation Research Part B: Methodological* 90, 192–217.



## Chapter 5

# Discussions and conclusions

## 5.1 Summary

This thesis was developed in the context of smart mobility, which encompasses many newly-emerged travel modes. The three papers included in this thesis all revolved around the theme of understanding individual mode choice behaviour when new modes come into play. The aim was to provide empirical evidence for mode choice behaviour in the new contexts, and moreover, to address the role of unique behavioural characteristics with respect to their introduction. This thesis examined novelty-seeking and alternation behaviour, both corresponding to a broader concept of variety-seeking, beyond the consumer marketing field and merged multiple types of preference elicitation data in understanding individuals' perceived attribute importance. In the process of realising the research targets, a number of methodological and applied contributions have been made. The research findings not only confirm the impact of novelty-seeking and alternation in mode choice behaviour but also illustrate the potential of combining data for better understanding of preferences towards various attributes.

This concluding chapter discusses how the original objectives have been accomplished, the contributions to practice and knowledge, and the outlook for future research directions.

## 5.2 Accomplishment of objectives

This section revisits the research objectives identified in the introduction chapter, provides links across different chapters, and summarises the progress made in achieving the objectives. Table 5.1 outlines the accomplishment of the objectives.

- **Objective O1: Developing a quantitative way to analyse the impact of novelty-seeking aspect of variety-seeking on individual mode choice behaviour**

**Table 5.1:** Accomplishment of objectives

Chapter	Research context	New mode	Data type	Factors investigated	Objective
Ch 2	Intermodal mobility	Integrated HSR-air	SC+rating	Novelty-seeking	O1
Ch 3	Shared mobility	Air taxi	SC+rating	Novelty-seeking+Alternation	O1+O2
Ch 4	Intermodal mobility	Integrated HSR-air	SC+BWS1+BWS2	Attribute importance	O3

As stressed in the introduction chapter, this thesis distinguished the impact of the two aspects of variety-seeking on mode choices. One aspect is novelty-seeking (i.e. the inclination to adopt new modes) and another aspect is alternation (i.e. the inclination to vary one's behaviour regularly by selecting different modes continuously).

The novelty-seeking effect (i.e. objective O1) was addressed in Chapters 2 and 3. Both chapters assumed that the underlying variety-seeking tendencies vary across respondents and are driven/reflected by novelty-seeking. Both chapters relied on stated choice (SC) data and attitudinal rating data to examine the impact of the novelty-seeking aspect of variety-seeking on mode choice behaviour. This examination was conducted through integrated choice and latent variable (ICLV) models, where the underlying construct of variety-seeking was treated as a latent variable which simultaneously explained the stated choices and responses towards the attitudinal rating tasks.

Aside from the shared similarities, these two chapters are different in terms of the research context. As mentioned in the introduction chapter, intermodal mobility and shared mobility are two representative facets of shared mobility. Given this, while Chapter 2 was set in the context of intermodal mobility and studied the mode choice behaviour after the new high-speed rail(HSR)-air intermodal service was involved in China, Chapter 3 took advantages of the burgeoning shared mobility services and explored people's inclination to adopt the new air taxi service in the U.S. Valid revealed preference (RP) data was difficult to obtain in both contexts as the relatively new HSR-air intermodal service was very unfamiliar to the general public during the survey period and the air taxi has not yet been launched.

These two chapters are also distinguished in the way that the latent variable was accommodated and the representation of preference heterogeneity. Chapter 2 accounted for the impact of variety-seeking within a standard ICLV model, assuming that part of preference heterogeneity across respondents could be explained by the latent variable of variety-seeking. Essentially, the latent variety-seeking was interacted with the alternative-specific constant (ASC) of each alternative in the utility functions of the choice model component, such that the different impact of variety-seeking on different alternatives could be analysed.

Chapter 3 addressed the impact of variety-seeking through a modified ICLV model (i.e. latent class model with a latent variable of variety-seeking). Specifically, this model presumes inter-respondent preference heterogeneity using a standard latent class model and additionally assumes that there is a probability that an individual exhibits intra-individual preference heterogeneity.<sup>1</sup> The latent variety-seeking did not directly enter the utility functions in the choice model, but instead was used to determine the class allocation functions in the choice model within a latent class framework, such that the probability of belonging to a specific class varied across respondents.

Although conducted in different contexts and within different discrete choice modelling frameworks, these two chapters converged with respect to the role of the novelty-seeking aspect of variety-seeking on mode choices. The modelling results of Chapter 2 suggested that stronger variety-seeking tendencies could lead to greater inclination to adopt the new HSR-air intermodal service. Similarly, the findings of Chapter 3 showed that stronger variety-seeking tendencies would result in higher propensity to fall into the class with higher willingness-to-adopt the new air taxi mode.

- **Objective O2: Developing a quantitative approach to account for the impact of alternation aspect of variety-seeking on individual mode choice behaviour**

Starting from the findings in respect of the influences of the novelty-seeking aspect of variety-seeking, this thesis continued the work on quantifying the alternation effect of variety-seeking and measuring its impact on mode choice behaviour.

As defined in section 1.2 of the introduction chapter, alternation aspect of variety-seeking refers to the tendency of switching choices among familiar alternatives as additional utility could be obtained from change itself, and this behaviour is usually revealed in longitudinal data. Nevertheless, this thesis attempted to explore the alternation effect in repeated SC tasks in a different way. That is, it postulated that alternation effect in SC survey could be reflected by the tendency of exhibiting unstable preferences across choice tasks. In this sense, this thesis made connections between the alternation aspect of variety-seeking and preference heterogeneity over choice tasks within a given individual, i.e. intra-individual preference heterogeneity. Following this strategy, Chapter 3

---

<sup>1</sup>Before adopting the latent class model, we had applied the standard ICLV model on the air taxi dataset and the results were accordant with Chapter 2. Chapter 3 structured the data within a latent class framework mainly to account for the alternation aspect of variety seeking.

accommodated the alternation aspect of variety-seeking on top of the novelty-seeking effect, such that addressed the objective O2 in addition to O1.

Prior to the work in Chapter 3, attempts had been made to uncover the relationship between alternation tendencies and intra-individual preference heterogeneity using the HSR-air intermodality data based on the work of Chapter 2. This initial work was presented at the International Association of Travel Behaviour Research (IATBR) in 2018. Following the conventional way of accounting for inter-and-intra individual preference heterogeneity (Hess and Giergiczny, 2015; Hess and Rose, 2009; Hess and Train, 2011), this work proposed a model based on the ICLV model in Chapter 2 by further incorporating an additional layer of random continuous distribution over choice tasks and interacting the variation of the intra-individual randomness with the latent variable of variety-seeking. This work aimed to test two hypotheses, i.e. 1) variety-seeking driven by alternation will reflect itself by having a high degree of intra-respondent heterogeneity; 2) variety-seeking driven by novelty-seeking leads to a higher tendency of selecting the new alternative. Evidence supporting novelty-seeking was found, whereas little evidence of the alternation effect was discovered. The modelling results suggested that the inter-and-intra individual heterogeneity was very hard to estimate, at least using the HSR-air intermodality data with limited sample size and using the two-layer mixed multinomial logit (MMNL) framework which restricted the number of random draws in estimation.

Having obtained the data on shared mobility services including the upcoming air taxi from Uber gave a good opportunity to examine the alternation aspect of variety-seeking in addition to the novelty-seeking aspect as this dataset contains much richer choice observations from respondents almost 20 times as much as the HSR-air intermodality dataset. Chapter 3 made use of this Uber data, and inspired by Hess (2014), proposed a new two-layer latent variable latent class (2L-LV-LC) model to link alternation effect with intra-individual preference heterogeneity. That is, the continuous distributions at both inter and intra layers in the MMNL framework were replaced with discrete distributions at both layers in a latent class framework. Individuals were probabilistically allocated between novelty-seeker and novelty-avoider classes, and then further probabilistically allocated between with-alternation and without-alternation subclasses. As the two steps of segmentation at inter-individual level were both functions of the latent variable of variety-seeking, the class allocation probabilities vary across individuals depending on the variety-seeking tendencies. The estimation was much faster than the IATBR work and the results showed that both novelty-seeking and alternation effects were relevant in mode choice decisions and were of significant



size. Specifically, stronger variety-tendencies were found driven/reflected by both stronger desire to seek novelty and higher probability to exhibit unstable preferences across choice tasks (i.e. with alternation effect). By comparing the market share of the new UberAIR alternative across different classes, it was discovered that novelty-seekers were more prone to adopt UberAIR than novelty-avoiders and that with-alternation individuals were also more likely to select UberAIR than without-alternation individuals.

- **Objective O3: Assessing attribute importance through different SP methods and examining the consistency of these methods in revealing individuals' perception of attribute importance in situations where individuals experience uncertainties caused by the introduction of the new and unfamiliar**

This objective was met in Chapter 4, which was also set in the context of HSR-air intermodal service in China as in Chapter 2. Given that the new HSR-air intermodal service exhibited new attributes and its entry could bring about uncertainties in the assessment of attribute importance when completing the SC survey, using multiple types of stated preference (SP) survey could give more behavioural information with respect to individuals' attribute processing, compared to presenting respondents with a longer SC survey with more number of SC tasks.

Chapter 4 therefore made use of the conventional SC data and best-worst scaling (BWS) data (including BWS case 1 data and BWS case 2 data) collected from the same sample. These three types of data were jointly estimated within a single modelling framework, with an aim to explore the consistency of different types of data in revealing attribute importance in mode choice behaviour at the individual level and to better understand choices made in the context of new alternatives.

Since the SC, BWS case 1 and BWS case 2 data are all typical methods to measure attribute importance, Chapter 4 synthesised these three types of data within an ICLV framework, where each attribute was associated with a specific latent variable of attribute importance, linking different types of data. Specifically, each type of data formed a separate modelling component, i.e. SC data in the choice model component, BWS case 1 data in the first measurement model component and BWS case 2 data in the second measurement model component. The latent variables of attribute importance, of which the values varied across respondents, were incorporated in each component (where applicable) to explain the preference heterogeneity across individuals in each type of data. The joint

model was constructed based on the hypothesis that stronger importance perceived from an attribute would lead the individual to be more sensitive to that attribute in SC tasks, attach higher weight on the same attribute in BWS case 1 tasks, and exhibit wider differences in terms of the attractiveness between different levels of that attribute than other individuals. The research findings confirmed this hypothesis and this consistency was especially strong for non-cost attributes, whereas a one-to-one relationship between different survey data was not found.

It needs to be noted that although Chapter 2 and Chapter 4 both used the HSR-air intermodality data, the research objective fulfilled was independent between these two chapters. That is, Chapter 4 did not account for the impact of the novelty-seeking aspect of variety-seeking (i.e. objective O1) and the role of attribute importance (i.e. objective O3) at the same time, but only addressed the latter. This limitation was mainly attributed to the limit sample size of the HSR-air intermodality data, which was collected by the PhD candidate alone and makes it difficult to account for all relevant factors within a single modelling framework. It is possible to expect that with a much larger sample, different effects could be captured simultaneously and these two objectives (even all the three objectives identified) could be accommodated altogether within a single framework.

## 5.3 Contributions

This thesis has made contributions around the theme of understanding mode choice behaviour when new smart mobility services are introduced. The key contributions to the practice of behavioural analysis and to the methodological knowledge in choice modelling are summarised in this section.

### 5.3.1 Practice

Two representative facets of smart mobility were chosen as the research contexts in this thesis, i.e. intermodal mobility and shared mobility. Integrated HSR-air service and air taxi service were the new modes involved in each context, both of which are expected to contribute to higher efficiency in transport system and easier travel experience for travellers. In this thesis, the impacts of various level-of-service attributes were illustrated, such as through the calculation of value of travel time and the willingness to pay for some “good”. For example, Chapter 2 found that when facing choices amongst the new HSR-air intermodal service and other existing modes, people showed greater sensitivities towards connection

time than to other types of travel time components. Integrated luggage handling system was more attractive to passengers with more than one piece of luggage and delay protection was more important for people who had never been to the transfer city. Nevertheless, no clear evidence was shown about the impact of the integrated ticketing system on mode choice decisions. Chapter 4 further showed that an individual with a stronger perception of the importance of a given attribute would lead to stronger sensitivity to that attribute than other individuals. Chapter 3 examined the choices amongst the upcoming air taxi service and other existing ground-based shared mobility services, and it discovered that passengers perceived higher value on egress time than on access time and in-vehicle/flight time.

Furthermore, the mode choice analyses in this thesis also took into account of the role of some unobserved psychometric factors, i.e. novelty-seeking, alternation and attribute importance, which could provide additional behavioural explanations behind mode choices when new modes are involved and contribute to better retrieve of preference heterogeneity. Chapter 2 and Chapter 3 extended the analysis on the two aspects of variety-seeking into the field of transport and in the SC environment. Both chapters discovered the positive relationship between variety-seeking tendencies and the inclination of adopting the new mode. In addition, Chapter 3 segmented individuals into different groups based on the variety-seeking tendencies, and the modelling results implied that on average, nearly 60% of individuals were affected by at least one of the two aspects of variety-seeking, with novelty-seeking aspect showing a lightly stronger impact than alternation aspect. Chapter 4 innovatively used BWS case 1 and BWS case 2 data to assist in exploring how the perception of the importance of attributes affects mode choice behaviour in SC tasks. The findings showed that the perception of attribute importance varied over individuals and that preference consistency could be discovered to a certain extent among different types of data.

As such, this thesis provided empirical insights to policymakers and practitioners in terms of improving travel services, forecasting travel demand and identifying potential customers. These empirical insights complemented the theoretical studies on the optimisation of transport operation. This bears particular significance nowadays as the urbanisation progress has resulted in negative externalities, such as traffic congestion and air pollution. Smart mobility is expected to ameliorate the deterioration, balance the conflict between growing travel demand and limited travel resources, and improve mobility for travellers. In this sense, understanding how people react in the new context of intermodal mobility and shared mobility and uncovering the travel demand of the new modes are of

great importance.

### 5.3.2 Methodology

In what follows, the methodological contributions made in this thesis are highlighted. Technology is advancing rapidly nowadays which has been hatching new ideas, products, services, etc., both within and beyond the transport realm, requiring empirical analysis to understand individual preferences and choice behaviour. These methodological contributions could be extended to applications in other relevant choice contexts.

#### 5.3.2.1 A context-specific psychometric scale to measure the unobserved variety-seeking tendency and an ICLV model to understand the inclination to adopt new modes

Chapter 2 developed psychometric scales based on relevant existing scales (e.g. variety-seeking, risk-taking, personality constructs, exploratory behaviour, arousal seeking and sensation seeking) to quantify the variety-seeking tendencies in a travel-related context. Since the impact of unobserved psychological factors including variety-seeking on decision-making is context-specific, it might cause bias to directly apply an existing scale on variety-seeking in the context of food consumption, brand switching, etc. in our travel behaviour analysis. Thus, the context-specific psychometric scales developed in this chapter is beneficial to the measurement of the unobserved variety-seeking tendencies in the context of new travel modes. This scale could be found in section 2.3.5.

Additionally, Chapter 2 established an ICLV model to address the impact of unobserved latent variety-seeking on the adoption of the new HSR-air intermodal service. In this model, the responses towards the attitudinal rating questions constituting the scales were not directly used as explanatory variables in the utility functions of the choice model, but were explained by the latent variable of variety-seeking in the measurement equations. By doing so, measurement errors arisen in answering the attitudinal rating tasks can be avoided, and endogeneity bias caused by the potential correlation between the responses towards these attitudinal tasks and stated choices could be avoided. This advantage has also been reflected in Chapter 3 and Chapter 4, both incorporating latent variables to account for the impact of unobserved factors.

### 5.3.2.2 A latent class model to account for the impact of novelty-seeking and alternation aspects of variety-seeking on mode choice behaviour

Chapter 3 established a latent class model with a latent variable of variety-seeking and used the latent variable to determine the class allocation probabilities through a two-step segmentation process. This model postulated that there existed two classes of respondents, one with higher willingness to adopt the new air taxi service and another with lower willingness, and that each of the two classes could be further segmented into two subclasses, one with stable preferences across stated choice tasks and another without.<sup>2</sup> With this, inter-individual preference heterogeneity could be accommodated. In the first step and second step of segmentation, the latent variable of variety-seeking was used as an explanatory variable with a step-specific coefficient capturing the impact of the novelty-seeking effect and the alternation effect, respectively. Since the latent variety-seeking varied across respondents, the probabilities of class allocation also differed across respondents.

This two-step segmentation at inter-individual level enabled classifying a sample based on multiple rules without the need to estimate too many class-specific parameters. Take the model in Chapter 3 as an example, each step of segmentation probabilistically divided the current object into two groups through a binary logit model, and only one group in each step needed to be specified with to-be-estimated parameters while the coefficients for another group were all fixed to 0 for normalisation. Thus two sets of parameters needed to be estimated and four groups could be obtained in total. In contrast, if we directly divide the original sample into four groups, then three sets of parameters need to be specified for estimation while the parameters for the remaining group are kept to 0.

This model also provided practical insights for policymakers and practitioners with respect to who are more/ less inclined to adopt the novel air taxi service in the future and who have greater/ less stability and consistency in their preferences across choice tasks. This is beneficial to the promotion of the new service.

---

<sup>2</sup>We appreciated the comment received on the 6<sup>th</sup> International Choice Modelling Conference, 19-21 August 2019, that there might be more than two classes (i.e. novelty-seekers and novelty-avoiders) of individuals in the population. We think it would be helpful to try with three (or more) classes so that those who do not seek or avoid novelties could be identified.

### 5.3.2.3 An innovative approach to accommodate inter-and-intra preference heterogeneity within a two-layer latent class model

As just mentioned in section 5.3.2.2, the new model put forward in Chapter 3 considered the two aspects of variety-seeking and the two-step segmentation captured heterogeneity of preferences across different classes of individuals. Specifically, the novelty-seeking tendencies were reflected by the differences in the choice probability of the new air taxi service (i.e. market share) in different classes. That is, the novelty-seeker class related to a higher probability to adopt the new air taxi service than the novelty-avoider class. Meanwhile, the alternation effect was illustrated by the average choice probability of the chosen alternation across tasks. That is, the class with alternation effect was associated with lower average probability for the chosen alternative, suggesting that the choices were less deterministic over tasks.

What makes this model innovative can be particularly illustrated by the way the alternation aspect was controlled. This was achieved at the intra-individual layer based on the assumption that alteration effect could be manifested by unstable preferences over choice tasks and that each individual had a probability to exhibit preference heterogeneity across choice tasks (i.e. intra-individual preference heterogeneity). The class with alternation effect was associated with an additional layer of discrete randomness in ASC across choice tasks, such that the ASC values for the class with alternation effect were not fixed but shifted around baseline values by alternative-specific variation terms.

Therefore, this model essentially replaced the continuous distributions over individual and over choice tasks proposed by [Hess and Rose \(2009\)](#) by discrete continuous distributions, respectively, which consequently could substantially reduce the computational burden in accommodating inter-and-intra individual preference heterogeneity.

### 5.3.2.4 Using an ICLV model to synthesise SC data, BWS case 1 data and BWS case 2 data within an ICLV modelling framework

The measurement model component of an ICLV model usually uses latent variables to explain the responses towards self-stated attitudinal rating questions, binary questions and raking tasks through ordered logit model, binary logit model and exploded logit model, respectively. However, there were no other studies which used BWS data in the measurement model component of an ICLV model. Nevertheless, BWS data is gaining increasing popularity outside of transport, particularly in marketing and health research to elicit preferences from individuals, and combining SC data with BWS data would mean an opportunity to

achieve better exploitation of behavioural information.

Chapter 4 constructed BWS case 1 data, BWS case 2 data together with SC data simultaneously within a single ICLV modelling framework where the two types of BWS data were used in the measurement model component. While the SC data was formalised with a logit kernel, the other two types of BWS data were both represented based on a MaxDiff criterion. The linkage of these three types of data was attribute importance, as these three types of data can all reveal individuals' perception of the importance of each attribute. In this model, each attribute was associated with a latent variable of attribute importance, which entered the choice model component for the SC data and the measurement model components for the BWS case 1 data and the BWS case 2 data. A side-product of this joint model is that it presented an alternative way to examine the consistency of perceived attribute importance between SC data and BWS data at the individual level. Although one-to-one relationship was not discovered, the way respondents made stated choices, reacted to BWS case 1 tasks and BWS case 2 tasks was relatively consistent. The combination of additional preference elicitation data with conventional SC data is beneficial to improve the behavioural explanatory power.

## 5.4 Future research avenues

This thesis has contributed to the exploration of mode choice behaviour when new modes come into play, and there remain a great number of relevant research areas to be analysed. This section outlines potential avenues for future research, revolving around a wider theme of understanding travel behaviour when new travel services are introduced.

The studies in this thesis were all based on SP data collected in hypothetical choice scenarios in a single setting when the mode of interest was very novel. This requires analyses on new data, especially collected from real-world market environment, for validation of and comparison with the findings of this thesis. For instance, previous research has studied the impact of inertia on adopting the new alternative by merging RP and SP data (e.g. [González et al., 2017](#)) or launching SP surveys before and after the implementation of the novel service (e.g. [Jensen et al., 2013](#)). In this thesis, although respondents were required to reveal the travel information of their most recent trip(s) in the HSR-air intermodality questionnaire and the air taxi questionnaire, the RP data was not used. This is attributed to the very insufficient use of the new integrated HSR-air mode in our sampled data for the research of HSR-air intermodality and the

unavailability of the upcoming UberAIR service for the study of air taxi during the data collection period. SP data is useful in providing insights regarding the preferences to the new attributes and the travel demand of the new modes, for which one cannot obtain based on RP data without the new modes. However, SP data has its own shortcomings as it is collected within hypothetical scenarios, which might lead to overestimation/ underestimation of the sensitivity to some attributes. Combining SP and RP data can improve evaluation of trade-offs, and more importantly, can lead to more reliable forecasting of travel demand in different future scenarios (Hensher et al., 1998; Louviere et al., 2000). Therefore, an obvious direction in the future is to conduct another round of survey (both SP and RP) when the HSR-air intermodality has become much more familiar to the general public or when the UberAIR service has been operated in the market for a relatively long time. Analysis can be done to compare the results with the studies of this thesis, to jointly estimate the before-and-after data, and to combine SP and RP data to facilitate demand prediction.

Besides, as time passes by, collecting longitudinal data at an individual level with respect to the decision of adopting a new mode is possible. With longitudinal RP data, we can analyse the adoption and diffusion of a new mode over time to examine how different factors determine whether or not to adopt the new mode and when to adopt the new mode, and to predict the demand for the new mode over time (e.g. El Zarwi et al., 2017). Apart from analysing the diffusion process of the new alternative, it is also worth investigating how strong individuals are adhesive to a new product after it has existed in the market for a period of time. Obviously, some products could initially be very attractive to customers, but this effect could not persist for long. Additionally, it would be of great interest to explore not only the impact of the intrinsic motives (such as the desire for the novelty and alternation) but also the role of social influence (such as social conformity or desire for distinction), as incorporating the social influence would lead to better prediction of travel demand over time.

Moreover, variety-seeking (alternation) behaviour in the consumer marketing studies has been described through calculating transition probabilities from one status to another different status (e.g. Borgers et al., 1989). It would also be worth formalising the representation of alternation within the domain of travel behaviour analysis. If longitudinal RP data can be obtained, the alternating process could be mathematically described over a period of time with respect to various types of travel behaviour, e.g. mode choice, route choice, vacation destination choice. This is useful in predicting individuals' future selection and travel demand. It would also improve the understanding of passengers' requirement



#### 5.4. Future research avenues

and preferences for the establishment of a comprehensive multi-modal transport system encompassing diverse smart mobility services.

Furthermore, it is reasonable to expect that different passengers would make choices among sets of different sizes as a result of the different variety-seeking (alternation) tendencies, such that additional research into the relationship between alternation and choice set consideration could be done.

Finally, although much effort has been made in comparing or combining BWS data with SC data in eliciting preferences, conclusions vary across contexts. As such, much more empirical work should be done to explore the formalisation of the choice behaviour in different types of BWS data as well as approaches for data synthesis.

## References

- Borgers, A., Van Der Heijden, R., Timmermans, H., 1989. A variety seeking model of spatial choice-behaviour. *Environment and Planning A* 21, 1037–1048.
- El Zarwi, F., Vij, A., Walker, J.L., 2017. A discrete choice framework for modeling and forecasting the adoption and diffusion of new transportation services. *Transportation Research Part C: Emerging Technologies* 79, 207–223.
- González, R.M., Marrero, Á.S., Cherchi, E., 2017. Testing for inertia effect when a new tram is implemented. *Transportation Research Part A: Policy and Practice* 98, 150–159.
- Hensher, D., Louviere, J., Swait, J., 1998. Combining sources of preference data. *Journal of Econometrics* 89, 197–221.
- Hess, S., 2014. 14 latent class structures: taste heterogeneity and beyond, in: *Handbook of choice modelling*. Edward Elgar Publishing Cheltenham, pp. 311–329.
- Hess, S., Giergiczny, M., 2015. Intra-respondent heterogeneity in a stated choice survey on wetland conservation in belarus: first steps towards creating a link with uncertainty in contingent valuation. *Environmental and Resource Economics* 60, 327–347.
- Hess, S., Rose, J.M., 2009. Allowing for intra-respondent variations in coefficients estimated on repeated choice data. *Transportation Research Part B: Methodological* 43, 708–719.
- Hess, S., Train, K.E., 2011. Recovery of inter-and intra-personal heterogeneity using mixed logit models. *Transportation Research Part B: Methodological* 45, 973–990.
- Jensen, A.F., Cherchi, E., Mabit, S.L., 2013. On the stability of preferences and attitudes before and after experiencing an electric vehicle. *Transportation Research Part D: Transport and Environment* 25, 24–32.
- Louviere, J.J., Hensher, D.A., Swait, J.D., 2000. *Stated choice methods: analysis and applications*. Cambridge university press.

## Appendix A

# Appendix to Chapter 2

### A.1 Screening criteria

The detailed screening flow chart is shown in Fig. A.1. In the end, 12 respondents in our final sample (N=123) were making domestic travel but had international travel experience before, while the other 111 respondents were travelling to or from international destinations. This sample allowed us to approach passengers who were familiar with nearby cities (within 210min by HSR) and had (or were going to have) experience of international travel. That is to say, the sampled respondents could well understand the new scenario incorporating HSR-air intermodality service.

### A.2 Identification of attributes

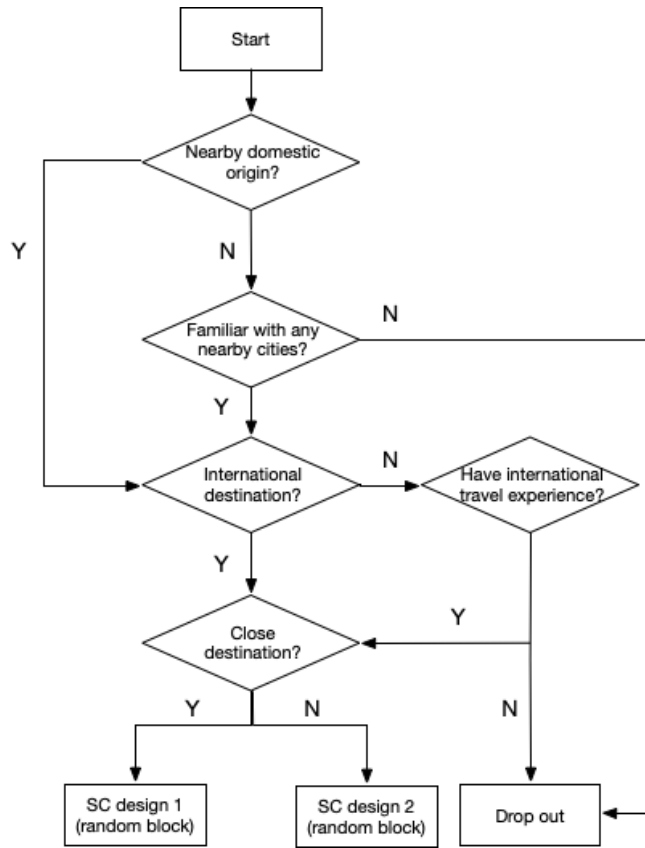
This section describes in details how the 7 attributes were identified to be involved in our final SC survey.

#### A.2.1 Step 1: Literature review

The first step is conducting literature review. The discussion from page 7 to Table 1.1 on page 9 has shown what attributes had been adopted in existing DCM-based mode choice studies. Apart from them, other studies have investigated what factors affect HSR-air intermodality service from a broader transport policy perspective. For example, Costa (2012)<sup>1</sup> summarised via literature review the influential factors including: travel time (e.g. access time, waiting time at the rail station, rail leg travel time, transfer time, air leg travel time, egress time), ticket price, ease of transfer (e.g. flight delays, train delays, baggage handling, waiting

---

<sup>1</sup>Costa, J., 2012. Factors of air-rail passenger intermodality (Doctoral dissertation, Dissertation submitted for obtaining the degree of Master in Territory Engineering, University of Lisboa, Lisboa).



**Fig. A.1:** Screening criteria in data collection.

time), ease of access/egress, marketing and passenger incentives (e.g. frequent flyer points), integrated ticketing, frequency schedule and capacity, reliability and punctuality and delay assistance, connection opportunities and passenger volumes, rail on-board comfort and customer service, security, governance, and legal and regulatory factors.

### A.2.2 Step 2: Preliminary BWS survey

Next, we launched a preliminary BWS case 1 survey to identify what attributes to be involved in the experimental design for the pilot SC survey. This additional preparatory research was required to ensure a proper set of attributes in the stated choice experiment. Moreover, only a limited number of mode choice studies had been conducted in the context of HSR-air intermodality, with most of them being set outside of China. Thus we need to focus on those representative attributes which are of the most concern from the perspective of Chinese passengers.

Balanced incomplete block design (BIBD) was adopted to design the preliminary BWS case 1 survey. A total of 16 items were selected as potential attributes according to relevant literatures and consultancy with other trans-

## A.2. Identification of attributes

port researchers. A design was generated in R containing 20 choice tasks per individual, all in a fixed size of 4. Each attribute appeared 5 times across the whole survey and each pair of attributes appeared once. In each choice task, a participant needed to pick both the most and least important attributes. The choice tasks were randomised across the whole survey and the attributes were randomised within each choice set. The data was collected between June 5th - 8th 2016 in China through an online questionnaire on the platform of Qualtrics, obtaining full responses from 173 individuals.<sup>2</sup>

Simple best-minus-worst scores were calculated as shown in Table A.1. The last column shows the best-minus-worst scores at the sample level. The counting results show that people value little about additional services, thus objects 6, 8 and 9 were dropped. Besides, although both “total travel time” and “flight time on major leg” were treated as being very important by the participants, they would not be involved as alternative attributes. This is because “total travel time” is made up of several time components, with “flight time on major leg” being the same across all alternatives in a certain choice task and not affecting the relative utility between alternatives. “Departure time” was dropped too as it could be closely correlated with other underlying factors out of the current investigation, e.g. “arrival time at destination”, creating ambiguity for respondents to evaluate its importance in comparison to other attributes and difficulties for us to design an experiment.

In order to further narrow down the attributes set, we tried to merge some objects. The correlation between each pair of objects is summarised in Table A.2. We found that: 1) Among those of which correlation coefficients exceed 0.3, “ticketing integration” and “luggage integration” were significantly correlated. This is in accordance with the reality since luggage integration would make no sense if the ticketing systems are not integrated. By combining the two factors, we had a new attribute called “integration level” which was no longer a binary variable, but with four levels in total: “full ticketing integration + luggage integration”, “full ticketing integration (allowed to buy tickets on third-party websites)”, “partial ticketing integration (only allowed to buy tickets on official airline websites)”, “no ticketing integration + no luggage integration”, coded as 4, 3, 2, 1, respectively. 2) “Access time” was correlated with “egress time” significantly. We decided to only keep the former as it is adopted more frequently in literatures than the latter. Additionally, we merged “refunding fare” and “delay protection” into a single attribute “delay protection” with three levels,

---

<sup>2</sup>This preparatory BWS survey approached more respondents than the final survey ( $N = 123$ ) mainly because the former was set up and circulated online with less strict screening criteria, whereas the latter was conducted via face-to-face interview.

**Table A.1:** Simple best-minus-worst scores at the sample level

Objects	Potential attributes	BEST	WORST	B-W
6	Frequent flyer point on HSR leg	37	569	-532
8	On-board service (e.g. catering)	57	528	-471
9	Seat comfort in the train	69	355	-286
10	Refunding fare	146	276	-130
16	Egress time at the destination	162	228	-66
1	Daily flight frequency on the minor leg	142	195	-53
11	Access time at the origin	200	220	-20
13	Travel time of minor (HSR) leg	178	129	49
3	Departure time at the station/ airport of the origin city	210	144	66
15	Flight time of major leg	217	141	76
4	Ticketing integration	272	143	129
5	Luggage handling integration	280	145	135
7	Delay protection	313	131	182
2	Travel cost	337	103	234
14	Layover between air and HSR	349	74	275
12	Total travel time	487	76	411

i.e. “free pre-travel reschedule + free flight change in case of HSR delay”, “free pre-travel reschedule + non-free flight change in case of HSR delay”, “non-free pre-travel reschedule + non-free flight change in case of HSR delay”, coded as 3, 2, 1, respectively.

In the end, seven attributes were identified via BWS study, i.e. : “layover”, “travel cost”, “delay protection”, “service integration”, “travel time of minor leg”, “access time” and “frequency on minor leg”.

### A.2.3 Step 3: Pilot SC survey

The choice experiment was designed through  $D$ -efficient approach based on the 7 attributes obtained in Step 2 and an additional attribute “parking fee” which was specific to the “car-air” alternative, i.e. 8 attributes in total. The data collection of this SC survey was conducted in July of 2016 at Hongqiao International Airport in Shanghai, China. The majority of the respondents were well-educated which was favourable as they would be more likely to better interpret the questionnaire and offer more reliable answers.

During the pilot survey, we also asked respondents to report whether each attribute involved in the SC tasks was considered. The results suggested that the consideration proportion declines in the sample in an order of “layover”, “travel cost”, “travel time on minor leg”, “delay protection”, “service integration”, “frequency on minor leg”, “access time”, “parking fee” and “other factors”.

Table A.2: Correlation matrix for BWS data

		HSRFrequency	TravelCost	TicketIntegration	LuggageIntegration	DelayProtection	Refunding	AccessTime	HSRTime	Layover	EgressTime
HSRFrequency	Pearson Correlation	1	-.201**	-0.102	-.166*	-0.099	0.063	-0.043	0.082	-0.001	-0.05
	Sig. (2-tailed)		0.008	0.181	0.029	0.194	0.412	0.571	0.284	0.987	0.515
TravelCost	Pearson Correlation	-0.201**	1	-0.135	-0.248**	-0.064	0.158*	0.027	-0.094	-0.147	-0.127
	Sig. (2-tailed)	0.008		0.077	0.001	0.404	0.038	0.725	0.217	0.054	0.097
TicketIntegration	Pearson Correlation	-0.102	-0.135	1	.371**	0.029	-0.125	-0.185*	-0.189*	-0.040	-0.269**
	Sig. (2-tailed)	0.181	0.077		0	0.704	0.101	0.015	0.013	0.598	0
LuggageIntegration	Pearson Correlation	-0.166*	-0.248**	0.371**	1	0.175*	-0.106	-0.203**	-0.202**	-0.021	-0.237**
	Sig. (2-tailed)	0.029	0.001	0		0.021	0.164	0.007	0.008	0.779	0.002
DelayProtection	Pearson Correlation	-0.099	-0.064	0.029	0.175*	1	0.209**	-0.240**	-0.309**	-0.005	-0.246**
	Sig. (2-tailed)	0.194	0.404	0.704	0.021		0.006	0.001	0	0.945	0.001
Refunding	Pearson Correlation	0.063	0.158*	-0.125	-0.106	0.209**	1	-0.240**	-0.105	0.021	-0.169*
	Sig. (2-tailed)	0.412	0.038	0.101	0.164	0.006		0.001	0.17	0.781	0.026
AccessTime	Pearson Correlation	-0.043	0.027	-0.185*	-0.203**	-0.240**	-0.240**	1	-0.039	0.128	0.447**
	Sig. (2-tailed)	0.571	0.725	0.015	0.007	0.001	0.001		0.615	0.094	0
HSRTime	Pearson Correlation	0.082	-0.094	-0.189*	-0.202**	-0.309**	-0.105	-0.039	1	-0.127	-0.068
	Sig. (2-tailed)	0.284	0.217	0.013	0.008	0	0.17	0.615		0.095	0.375
Layover	Pearson Correlation	-0.001	-0.147	-0.040	-0.021	-0.005	0.021	0.128	-0.127	1	0.03
	Sig. (2-tailed)	0.987	0.054	0.598	0.779	0.945	0.781	0.094	0.095		0.698
EgressTime	Pearson Correlation	-0.05	-0.127	-0.269**	-0.237**	-0.246**	-0.169*	0.447**	-0.068	0.03	1
	Sig. (2-tailed)	0.515	0.097	0	0.002	0.001	0.026	0	0.375	0.698	

\*\*Correlation is significant at the 0.01 level (2-tailed).

\*Correlation is significant at the 0.05 level (2-tailed).

An initial basic MNL model was estimated on 33 respondents with 330 observations in total. This was discussed in my PhD Transfer Report. The estimation results suggested that only minor time, travel cost, layover, frequency, and the highest level of delay protection were statistically significant, while the other integration-related parameters were not (see the left part of Table A.3).

After the PhD Transfer viva, we continued to improve the experimental design for the formal SC survey based on the reflections gained from the pilot SC survey, by modifying the incorporated attributes and attribute levels as well as refining utility specifications in the new experimental design. In particular, we divided “layover” into “connection time” and “transfer time” with the former stressing on time spent on waiting and the latter on time spent on moving between train station and airport. We expected to capture the value of different types of time. Also, “service integration” was split into “ticketing integration” and “luggage integration” with an aim to better understand the willingness to pay for different components of the integrative service. “Delay protection” was also simplified as the current levels appeared to be not easy for respondents to differentiate apart. We dropped “frequency on minor leg”, “access time” and “parking fee” as they were much less considered by respondents according to the statements from them.

In the end, 7 attributes were identified for the formal SC survey, i.e. “travel time on minor leg” (called “minor time” for short), “connection time”, “transfer time”, “delay protection”, “ticketing integration”, “luggage integration” and “travel cost”.

### A.3 Experimental design for formal SC survey

Two experimental designs were created using  $D$ -efficient design through the software Ngene, drawing priors from the pilot SC survey which are shown in the right part of Table A.3. The values of these priors are sourced based on the estimates of the initial MNL model shown in the left part of the same table. Since the attributes and levels used for the formal SC experimental design are not identical to those involved in the pilot SC survey, the values of priors are not exactly the same as the estimates of the initial MNL model on the pilot SC data. Instead, the initial MNL estimates were used to provide information of the expected signs of parameters and a rough idea of the values of priors.



**Table A.3:** Initial MNL estimates using data of the pilot SC survey and priors used in the design for the formal SC survey

Parameters in initial MNL on pilot SC data	est.	s.e.	<i>t</i> -rat.	Parameters for formal SC design	Prior value	<i>S</i> estimate (design1)	<i>S</i> estimate (design2)
$\beta_{MinorTime}$	-0.012	0.00	-2.89	$\beta_{MinorTime\_car}$	-0.010	1.30	1.46
$\beta_{Layover}$	-0.009	0.00	-3.76	$\beta_{MinorTime\_air}$	-0.018	3.94	3.34
$\beta_{logFrequency}$	0.392	0.17	1.99	$\beta_{MinorTime\_hsr}$	-0.012	1.64	1.37
$\beta_{DelayProtection=lv3,selfpaid}$	0.824	0.33	2.80	$\beta_{ConnectionTime\_air}$	-0.006	1.43	1.78
$\beta_{DelayProtection=lv3,reimbursed}$	-0.820	0.74	-1.45	$\beta_{ConnectionTime\_seprated}$	-0.010	3.06	3.93
$\beta_{DelayProtection=lv2,selfpaid}$	0.563	0.32	1.53	$\beta_{ConnectionTime\_integrated}$	-0.008	1.72	2.38
$\beta_{DelayProtection=lv2,reimbursed}$	-1.987	1.08	-1.87	$\beta_{TransferTime}$	-0.006	3.91	5.03
$\beta_{ServiceIntegration=lv4,experienced}$	-0.353	0.52	-0.71	$\beta_{DelayProtection=lv3}$	0.650	2.60	3.97
$\beta_{ServiceIntegration=lv4,inexperienced}$	0.458	0.36	1.28	$\beta_{DelayProtection=lv2}$	0.400	6.78	9.46
$\beta_{ServiceIntegration=lv3}$	0.551	0.35	1.68	$\beta_{TicketIntegration=lv3}$	0.700	6.78	7.79
$\beta_{ServiceIntegration=lv2}$	0.188	0.29	0.61	$\beta_{TicketIntegration=lv2}$	0.500	14.69	13.16
$\beta_{TravelCost}$	-0.003	0.00	-4.19	$\beta_{LuggageIntegration=lv3\_air}$	0.500	7.70	7.82
$ASC_{ca}$	-0.348	0.90	-0.37	$\beta_{LuggageIntegration=lv3\_integrated}$	0.800	7.35	8.01
				$\beta_{LuggageIntegration=lv2\_integrated}$	0.640	9.25	11.30
				$\beta_{TravelCost}$	-0.002	1.40	1.83

4 alternatives together with 7 attributes are involved in both designs. Choice scenarios in each design were segmented into 5 blocks, and each survey participant was randomly assigned to one of the blocks with 8 SC tasks shown in random order. The major difference between the two designs are the range of attribute levels for travel cost, that the attribute of travel cost in Design 1 was kept at a relatively lower level than in Design 2. Full description of the choice scenarios in these two SC experimental designs are summarised in Table A.4 and Table A.5. For brevity, some acronyms are used for the attributes in these two tables, such that: MT (minor time/ min), CT (connection time/ min), TT (transfer time/ min), DP (delay protection), TI (ticket integration), LI (luggage integration) and TC (travel cost/ CNY¥).

The attributes of minor time, connection time, transfer time and travel cost were treated as continuous variables. The attributes of delay protection, ticket integration and luggage integration were dummy coded categorical variables, with a bigger number representing a stronger level of the associated attribute. What each level of the categorical attributes stands for was elaborated in section 2.3.4. Some constraints were also imposed to ensure the choice scenarios to be reasonable and to avoid dominant options in choice tasks. For example, the minor time for the air-air alternative was restricted to be lower than the minor time for the alternatives related to HSR; the connection time for the separated HSR-air alternatives was restricted to be not higher than that for the air-air or integrated HSR-air alternatives as the separated one was considered to be more flexible than air-air and integrated HSR-air; if the cost of integrated HSR-air was much more expensive than the separated HSR-air, the connection time of the former could not be too long; in case the highest level applied to ticket integration, the cost of integrated HSR-air had to be higher than separated HSR-air. Different designs had been tested, and what shown in Table A.4 and Table A.5 are the ones with the lowest  $D$ -error while the  $S$ -estimate being kept as low as possible (ChoiceMetrics, 2012).<sup>3</sup>

---

<sup>3</sup>ChoiceMetrics, C., 2012. Ngene 1.1. 1 user manual & reference guide. Sydney, Australia.

**Table A.4:** Experimental design for SC survey 1

Choice situation	car-air		air-air						separated HSR-air				integrated HSR-air						Block	
	MT	CT	MT	CT	TT	DP	LI	TC	MT	CT	TT	TC	MT	CT	TT	DP	TI	LI		TC
1	210	1850	80	210	90	1	0	1350	120	120	0	1400	150	180	0	0	2	1	1250	1
2	180	2100	80	270	0	0	2	1350	120	60	90	1400	90	120	90	2	1	2	1450	3
3	270	1250	80	210	90	0	0	1050	180	30	90	1150	150	90	90	1	3	1	1250	1
4	240	1550	50	270	90	2	2	1050	90	0	0	1400	120	120	0	0	1	1	1250	3
5	300	1250	90	150	0	2	0	1050	150	0	90	1150	150	60	90	1	2	2	1250	4
6	240	2350	70	330	45	1	0	2000	90	0	0	2150	120	240	0	2	1	2	2050	1
7	270	1550	90	210	0	1	0	1350	120	120	0	1150	120	180	0	0	2	2	1450	2
8	180	2100	60	330	45	0	2	1600	90	120	0	1400	120	120	0	1	1	0	1450	2
9	300	2350	80	90	90	2	0	1600	210	60	0	1900	210	60	0	1	2	2	2050	3
10	210	2350	50	330	45	1	0	1600	150	120	0	1650	180	120	0	0	3	2	2050	4
11	270	1850	80	210	90	2	0	1800	210	90	90	1650	210	180	90	0	3	1	1700	2
12	300	2100	80	210	45	0	0	2000	210	0	45	1900	180	120	45	1	1	1	2050	4
13	180	1850	90	150	45	1	0	1050	120	0	45	1150	150	90	45	2	2	1	1450	3
14	240	2350	50	210	90	2	2	1800	120	60	0	2150	90	180	0	1	2	2	2250	2
15	270	1550	70	330	90	0	2	1350	210	0	90	1400	180	120	90	1	1	0	1450	1
16	270	2350	60	330	0	2	0	2000	180	60	45	2150	180	180	45	0	1	1	2250	1
17	270	1850	80	90	0	2	2	1350	180	0	45	1150	210	60	45	1	2	2	1250	1
18	300	2350	70	210	45	0	2	2000	180	30	0	1900	180	60	0	2	2	2	2250	2
19	270	1550	90	90	0	0	2	1050	210	30	45	1400	180	60	45	2	1	0	1450	4
20	240	1850	60	270	45	1	2	1600	120	0	0	1400	120	240	0	2	1	1	1450	5
21	210	1850	80	90	0	1	2	1050	90	0	90	1400	90	60	90	2	2	1	1450	1
22	180	2100	70	330	0	0	0	1600	90	120	0	1650	90	240	0	2	1	0	1450	2

(Continued on the next page)

**Table A.4:** Experimental design for SC survey 1 (continued)

Choice situation	car-air		air-air						separated HSR-air				integrated HSR-air						Block	
	MT	CT	MT	CT	TT	DP	LI	TC	MT	CT	TT	TC	MT	CT	TT	DP	TI	LI		TC
23	300	1250	70	330	45	0	0	1050	150	0	45	1150	120	180	45	1	3	2	1250	4
24	270	2350	60	330	0	1	0	2000	210	30	0	2150	210	180	0	0	1	2	2250	2
25	300	2350	70	330	0	1	0	2000	150	0	0	2150	180	120	0	2	1	1	2050	5
26	270	1550	70	210	45	1	2	1350	150	60	45	1150	120	90	45	0	3	2	1250	2
27	270	2350	60	330	0	2	0	2000	120	30	90	2150	90	60	90	1	1	1	2250	3
28	210	2100	50	330	0	2	2	1600	150	30	90	1400	120	120	90	0	3	2	1700	1
29	180	2350	50	330	90	1	0	2000	120	90	90	1900	90	240	90	0	3	2	2050	5
30	270	1250	70	270	0	0	0	1050	180	30	0	1150	210	90	0	2	3	2	1250	5
31	180	2350	80	270	90	0	0	1800	120	90	90	1650	150	180	90	1	3	1	1700	4
32	180	2350	70	210	45	0	2	1800	120	30	45	1900	150	60	45	1	2	1	1700	5
33	240	1850	60	270	45	2	2	1600	120	60	45	1650	90	240	45	1	3	1	1700	5
34	270	2350	70	90	90	1	2	2000	180	30	0	1900	150	60	0	2	3	1	2250	3
35	210	2350	50	330	0	1	2	1800	90	90	90	1900	120	180	90	0	2	2	1700	4
36	270	1250	90	150	90	0	0	1050	210	90	90	1150	210	120	90	2	1	0	1250	5
37	300	2350	70	150	0	0	2	1800	180	90	45	1650	210	120	45	2	3	1	2050	3
38	210	1550	80	330	45	2	0	1050	150	60	0	1150	120	90	0	1	1	2	1250	3
39	210	1850	80	150	90	2	2	1350	90	60	0	1150	120	120	0	0	1	1	1250	5
40	240	1850	90	90	0	2	0	1600	180	30	45	1650	150	60	45	0	2	1	1450	4

**Table A.5:** Experimental design for SC survey 2

Choice situation	car-air		air-air						separated HSR-air				integrated HSR-air						Block	
	MT	CT	MT	CT	TT	DP	LI	TC	MT	CT	TT	TC	MT	CT	TT	DP	TI	LI		TC
1	300	4550	90	150	45	1	0	4350	150	0	45	4150	120	60	45	1	2	2	4450	1
2	210	5350	80	330	45	0	2	5000	150	60	45	5150	120	60	45	0	1	0	5050	3
3	270	5100	70	90	90	0	2	4600	180	60	0	4400	150	60	0	1	2	1	4450	5
4	270	4850	70	330	0	1	0	4800	120	0	45	4650	90	90	45	2	1	1	4700	3
5	300	5350	80	90	45	1	0	4600	180	0	45	4900	210	60	45	2	1	0	4700	1
6	180	4250	60	330	45	2	0	4050	90	120	0	4150	120	120	0	0	3	1	4250	2
7	300	5100	60	270	90	1	2	4600	210	60	90	4650	210	120	90	0	1	2	4700	4
8	300	4550	50	330	90	1	0	4350	210	30	0	4150	210	120	0	0	2	2	4250	1
9	270	5350	50	330	90	0	0	5000	210	90	90	5150	180	240	90	0	2	2	5050	2
10	210	5350	80	330	45	1	0	4800	90	120	0	4900	120	240	0	1	1	1	4700	3
11	210	4850	60	270	0	1	2	4350	90	30	45	4400	90	240	45	0	3	1	4450	4
12	270	5100	90	210	90	0	2	4600	150	90	0	4900	150	120	0	2	1	1	5050	5
13	240	5100	70	210	45	0	2	4350	150	60	0	4400	180	90	0	1	1	2	4450	1
14	240	5100	50	330	0	2	2	5000	90	0	45	4900	120	120	45	0	2	1	5050	4
15	180	4250	90	150	45	0	0	4050	120	30	45	4150	120	60	45	1	2	1	4250	2
16	240	5350	70	210	0	2	2	4800	90	60	90	4900	90	90	90	1	1	0	4700	4
17	270	5350	50	210	90	2	2	4800	210	90	0	5150	210	120	0	1	2	2	5250	1
18	180	4850	80	270	45	2	2	4050	90	90	0	4400	90	240	0	2	1	1	4450	3
19	240	5350	90	90	90	0	0	4600	120	0	90	4900	150	60	90	0	1	2	5050	4
20	240	4850	80	90	90	2	0	4050	180	30	0	4400	150	60	0	0	1	1	4250	5
21	270	4850	60	210	0	0	2	4600	210	60	0	4400	210	180	0	0	2	2	4700	3
22	180	4550	70	330	90	0	0	4050	90	90	90	4150	120	120	90	1	1	2	4450	5

(Continued on the next page)

**Table A.5:** Experimental design for SC survey 2 (continued)

Choice situation	car-air		air-air						separated HSR-air				integrated HSR-air						Block	
	MT	CT	MT	CT	TT	DP	LI	TC	MT	CT	TT	TC	MT	CT	TT	DP	TI	LI		TC
23	180	4850	60	150	0	0	2	4350	120	0	90	4650	90	90	90	2	3	2	4700	1
24	300	5350	90	90	0	0	2	4600	180	30	90	4650	180	60	90	0	1	0	5050	1
25	240	4250	80	270	90	1	0	4050	150	90	90	4150	180	120	90	2	1	0	4250	2
26	270	5350	80	150	0	2	0	4800	180	0	0	5150	180	90	0	2	3	1	5250	4
27	240	5350	50	330	0	1	0	4800	120	30	90	4900	90	60	90	1	3	1	5250	2
28	300	4250	80	150	0	1	0	4050	210	0	0	4150	180	90	0	2	2	1	4250	5
29	300	4850	50	330	0	2	0	4050	180	120	0	4150	210	180	0	2	3	1	4250	5
30	300	4250	80	270	45	0	2	4050	150	90	45	4150	150	240	45	0	3	2	4250	4
31	240	5100	70	270	0	1	2	4800	180	30	0	4650	150	180	0	0	3	1	4700	2
32	180	4550	70	150	90	1	2	4050	120	0	0	4150	90	120	0	0	3	2	4250	2
33	210	5350	60	330	45	1	0	4800	120	30	45	5150	90	90	45	1	1	2	5250	5
34	270	5350	50	330	90	2	2	4800	150	90	90	4900	180	90	90	1	2	1	5250	3
35	180	4550	80	210	0	2	2	4350	120	30	45	4150	120	180	45	2	2	2	4250	3
36	210	5350	60	270	45	1	0	4800	90	120	0	4900	120	120	0	1	1	0	5050	3
37	210	5350	70	330	45	2	0	5000	120	90	0	4900	90	240	0	2	2	2	5250	1
38	270	5350	60	270	0	1	2	4800	180	30	45	5150	150	120	45	2	2	1	5050	4
39	210	5100	90	270	0	2	0	4350	150	120	45	4650	180	180	45	2	3	2	4700	2
40	270	5350	80	330	0	2	0	5000	210	90	90	4900	210	120	90	1	3	1	5250	5

## A.4 An example of questionnaire in the formal survey

Hello! I am Fangqing from the Institute for Transport Studies at the University of Leeds (UK). I am currently doing my PhD research on high-speed rail (HSR) and air travel. In recent years, there is an emerging new mode of travel called HSR-air intermodality, which enables passengers to jointly use HSR and air travel for a single journey without the hassles to purchase tickets separately to reach somewhere that is not accessible by direct flights or trains. This service has already been launched in Shanghai and its nearby areas. I am inviting you to take part in this survey to help us better understand mode choice behaviour and passengers' preferences in this new context. This questionnaire is made up of 7 sections and takes you around 30 minutes to complete. All the information you provide would be guaranteed anonymous, securely stored and for research use only. There is no way we can connect your responses with your personal identity or other confidential information. Thank you very much.

### Part 1: Current trip information

1. Where is the origin city of your current journey?
2. Where is the destination city of your current journey?
3. How familiar are you with the origin city?
  - Not familiar
  - Neutral
  - Familiar
4. How familiar are you with the destination city?
  - Not familiar
  - Neutral
  - Familiar
5. What is your travel purpose?
  - Holiday
  - Visit families or friends
  - Business

- Study abroad
  - Others
6. Are you travelling on your own?
- Yes
  - No
7. Can you get reimbursed from your current journey?
- Yes
  - No
8. How many pieces of luggage are you going to check in?
- 0
  - 1
  - >1
9. By which mode did you access Pudong International Airport?
- Public transport (e.g. bus, metro)
  - Private vehicle
  - Taxi
  - TNC (e.g. Didi)
  - Walk or bicycle
  - HSR
  - Air
  - Coach
  - Other
10. How long did it take you to access the airport?
- <30min
  - 30min-1h
  - 1h-2h
  - 2h-3h
  - >3h



## Part 2: Travel experience

1. Have you ever tried HSR-air intermodal service?
  - Yes
  - No
  
2. Which of the following can best describe your car ownership status?
  - No car in my household
  - Car is available in my household, but I do not drive
  - Car is available in my household, and I drive
  
3. For which reason do you drive the most? [if the third option is selected in the last question]
  - Commute
  - Holiday
  - I just enjoy driving and I drive whenever I can
  
4. Which mode do you prefer the most for intercity travel?
  - Car
  - Air
  - Train
  - No preference
  
5. How frequent do you fly in the recent two years?
  - 0
  - Once every year
  - Once every season
  - Once every month
  - Once every week or more frequent
  
6. How frequent do you take HSR trains in the recent two years?
  - 0
  - Once every year
  - Once every season

- Once every month
- Once every week or more frequent

7. How familiar are you with Shanghai?

- Not familiar
- Neutral
- Familiar

8. Which other mode(s) have you used to depart from or arrive at Shanghai?  
(multiple choices)

- This is my first time in Shanghai
- Car
- HSR
- Air
- Coach
- Other

9. Please reveal the details of your most recent medium-long-distance intercity travel. (5 tasks like this)

- Origin: \_\_\_\_\_
- Destination: \_\_\_\_\_
- Total travel time: \_\_\_\_\_
- Mode(s): \_\_\_\_\_

10. How long the layover can you bear at most? (assuming the layover cannot go below 1.5h due to the schedule coordination between HSR and air and time spent on transfer)

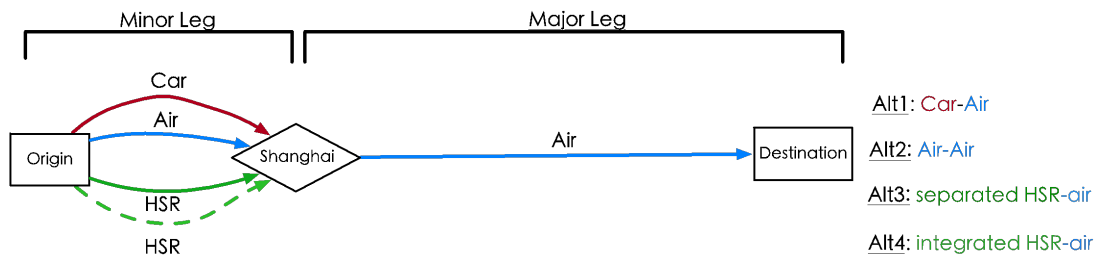
- 1.5h
- 2h
- 2.5h
- 3h
- 3.5h
- 4h
- 4.5h

- 5h
11. How early do you usually arrive at a departing airport prior to the departure time? (assuming passengers need to arrive at least 1.5h before the departure time due to the procedures like luggage check-in and security check)
- 1.5h
  - 2h
  - 2.5h
  - 3h
  - 3.5h
  - 4h
  - 4.5h
  - 5h

### Part 3: SC tasks

In this section, 8 choice tasks will be presented, all independent from each other. Each choice task includes four alternatives, which are: car+air, air+air (connecting flights), separated HSR+air (traditional mode), integrated HSR+air (new mode). Each alternative will be described by several attributes.

Assumes that Shanghai is the transfer city, the origin city can be accessed by HSR within 210min (e.g. Nanjing, Hefei), the destination is a nearby international city (e.g. Tokyo, Osaka). No direct flight is available between the origin and the destination, thus passengers need to transfer at Shanghai. “Shanghai to destination” is the major leg and can only travel by air; whereas “origin to Shanghai” is the minor leg which can be travelled by car, air or HSR. The minimum connection time is assumed to be 1.5h due to essential procedures including security check, etc.



1. Please choose your most preferred option in the following scenario. (There are 8 choice tasks like this for each respondent.)

## Appendix A. Appendix to Chapter 2

	Car-air	Air-air	Separated HSR-air	Integrated HSR-air
Travel cost	¥1,250	¥1,050	¥1,150	¥1,250
Minor time	5h	1.5h	2.5h	2.5h
Transfer time	0h	0h	1.5h	1.5h
Connection time	1.5h	4h	1.5h	2.5h
Delay protection	None	Free flight change	None	50% discount on changing flight
Ticket integration	-	<ul style="list-style-type: none"> <li>• <i>Book together</i></li> <li>• <i>Fixed-time flight on minor leg</i></li> <li>• <i>Easy collection</i></li> </ul>	<ul style="list-style-type: none"> <li>• <i>Book separately</i></li> <li>• <i>Fixed-time train on minor leg</i></li> <li>• <i>No easy collection</i></li> </ul>	<ul style="list-style-type: none"> <li>• <i>Book together</i></li> <li>• <i>Fixed-time train on minor leg</i></li> <li>• <i>Easy collection</i></li> </ul>
Security check and luggage integration	-	<ul style="list-style-type: none"> <li>• <i>Two security checks</i></li> <li>• <i>No integrated luggage handling system</i></li> </ul>	<ul style="list-style-type: none"> <li>• <i>Two security checks</i></li> <li>• <i>No integrated luggage handling system</i></li> </ul>	<ul style="list-style-type: none"> <li>• <i>One security check</i></li> <li>• <i>Integrated luggage handling system available</i></li> </ul>

- Car-air
- Air-air
- Separated HSR-air
- Integrated HSR-air

### Part 4: BWS1 tasks

1. If you are now going to make a journey and integrated HSR-air mode is available, which factor do you think matter the most and least to you? (there are 7 BWS1 tasks like this.)

Most important	Least important
○ Minor time	○
○ Delay protection	○
○ Connection time	○
○ Travel cost	○

### Part 5: BWS2 tasks

1. Assume there is an integrated HSR-air service which costs 1700RMB in total, takes 3.5h by HSR train on the minor leg, and requires 1.5h to transfer from Hongqiao HSR station to Pudong International Airport to catch the flight on the major leg. The other characteristics of this service

#### A.4. An example of questionnaire in the formal survey

are shown below. Which ones are the most and least appealing to you?  
(there are 8 choices like this)

Most important		Least important
<input type="radio"/>	Connection time=2.5h	<input type="radio"/>
<input type="radio"/>	50% off on changing flight	<input type="radio"/>
<input type="radio"/>	Book together, fixed-time train on the minor leg, and easy collection	<input type="radio"/>
<input type="radio"/>	Integrated luggage-handling and one security check	<input type="radio"/>

### Part 6: Attitudinal statements

Please indicate which score best describes your agreement with the presented attitudinal statement. There are 17 attitudinal questions in total.

1. "I am the kind of person who would try new products even if I'm satisfied with my current purchasing"
  - strongly disagree
  - disagree
  - slightly disagree
  - neutral
  - slightly agree
  - agree
  - strongly agree

### Part 7: Socio-demographic information

This is the last part of this questionnaire, which requires you to provide your socio-demographic information. Confidential personal information will not be asked and all your data is guaranteed anonymous, to be securely stored and for research use only.

1. Your gender
  - Male
  - Female
2. Your age
  - <23

- 23-35
- 36-45
- 46-60
- >60

3. Your education

- Elementary level or below
- Secondary level
- Graduated from technical school
- Bachelor's degree (obtained/reading)
- Master's degree or above (obtained/reading)

4. Your after-tax annual income

- <50,000
- 50,000-100,000
- 100,000-150,000
- 150,000-200,000
- 200,000-250,000
- >250,000

5. Your employment

- Student
- Work for government department or institutions
- Work for company
- Self-employed
- Freelancer
- Retired/unemployed
- Others

6. Do you hold a valid Chinese national identification card?

- Yes
- No

## Appendix B

# Appendix to Chapter 4

## B.1 Experimental design for the BWS case 1 survey

In the formal questionnaire, the SC survey was followed by a BWS case 1 survey and a BWS case 2 survey. The BWS case 1 survey for was created through the balanced incomplete block design (BIBD). A total number of 7 attributes were allocated into 7 choice sets, each with 4 attributes. Each attribute occurred 4 times and co-occurred twice with any other attribute throughout the survey. The choice tasks were shown to individuals in randomised order. The full description of this design is shown as below:

**Table B.1:** Experimental design for BWS case 1 survey

Task	Attribute 1	Attribute 2	Attribute 3	Attribute 4
1	minor time	connection time	delay protection	travel cost
2	minor time	connection time	transfer time	luggage integration
3	transfer time	delay protection	luggage integration	travel cost
4	minor time	delay protection	ticket integration	luggage integration
5	connection time	ticket integration	luggage integration	travel cost
6	connection time	transfer time	delay protection	ticket integration
7	minor time	transfer time	ticket integration	travel cost

## B.2 Initial analyses for the TRB paper

Prior to the work presented in Chapter 4, an exploratory study was conducted in 2017 which was accepted for presentation on the 2018 Transportation Research Board (TRB) Annual Meeting. This study only made use of SC data and BWS case 1 data, without the incorporation of BWS case 2 data. The quantitative analysis in the TRB paper included three parts. Firstly, the individual-level

simple best-minus-worst (B-W) scores were calculated and compared against observed choices. Secondly, a Bayesian estimation was conducted to obtain the posterior marginal utilities for each attribute at the individual level in the SC data, which were then compared against the individual-specific B-W scores in BWS case 1 data. Thirdly, a preliminary ICLV model was established to jointly estimate the SC data and B-W scores in the BWS case 1 data. The remainder of Appendix B.2 are excerpted from the TRB paper, focusing on the three parts of quantitative analysis.

It needs to be noted that although the adopted data, model specifications and estimation results in Chapter 4 are not exactly the same as in the preliminary TRB paper, both works demonstrate the correlation between SC responses and BWS responses, and illustrate the differences between different preference elicitation methods.

In particular, the preliminary analysis included in the earlier TRB paper on B-W scores for BWS case 1 data is now attached in Appendix B.2.1 and Appendix B.2.2. It provides more evidence on the correlation between BWS and SC responses, which justifies the data synthesis. Meanwhile, it also supports the argument that SC and BWS surveys should not be regarded as equivalent as a respondent may rank an attribute as important in a mono-alternative setting (e.g. BWS case 1 tasks), but the impact on choices will depend on the specific values taken by the attribute within a multi-alternative setting (i.e. one-to-one relationship is not discovered).

Moreover, Appendix B.2.3 provides a preliminary joint estimation between SC data and BWS case 1 data which used individual-level simple best-minus-worst scores (i.e. subtracting the count of an item being selected as the worst from the count of an item being selected as the best) to reflect the importance perceived from each attribute for each respondent. In contrast, Chapter 4 explains the BWS case 1 choices via a MaxDiff model, further incorporates the BWS case 2 data and allows for more flexible modelling specifications (e.g. scale difference between the best and the worst choice stages is considered). Hence, the work in Chapter 4 is considered to be more capable in illustrating the relationships between different types of BWS data and SC data, and improving the understanding of choices in the new context of the introduction of new modes with the help of additional BWS case 1 and case 2 data.



### B.2.1 Analysis I: descriptive comparison between B-W scores and choice behaviour

We next conduct a comparative analysis between the individual-specific B-W scores and the observed choice outcomes. We look at the frequency of choosing the alternative with the lowest minor time, the one with the lowest connection time, the one with the lowest transfer time, and so forth. We do not find very strong correlation between the B-W scores and these choice strategies, but the weak links between the two can still provide us with some useful indications about attribute importance (the correlation coefficients mentioned below are all significant at 95% confidence level). It should be noted here that obviously more than one can apply at the same time in one choice (e.g. the fastest may also have the shortest connection time). We see that the B-W score on delay protection is positively correlated with the frequency of choosing the highest delay protection ( $\rho = 0.29$ ); the B-W score on luggage integration is positively correlated with the frequency of choosing the highest luggage integration ( $\rho = 0.17$ ), and negatively correlated with the frequency of choosing the lowest travel cost ( $\rho = -0.25$ ). This means that those who have higher B-W scores on delay protection are more frequently observed to choose the alternative with the highest level of delay protection; and respondents with higher B-W scores on luggage integration choose the alternative that can provide best integration service more often, and meanwhile care less about travel cost.

We also compare the individual-specific B-W scores against the frequency of each alternative being chosen in the SC survey. Again, only weak but significant correlation is detected where some useful implication can still be extracted. Firstly, it is discovered that the B-W score on connection time is positively correlated with the frequency of the separated HSR-air alternative being chosen in the SC tasks ( $\rho = 0.33$ ), and negatively correlated to the choice frequency for any of the other three alternatives (car-air:  $\rho = -0.16$ ; air-air:  $\rho = -0.18$ ; integrated HSR-air:  $\rho = -0.19$ ). Second, higher counts on luggage integration is related to lower frequency of choosing separated HSR-air ( $\rho = -0.32$ ) and higher frequency of choosing integrated HSR-air ( $\rho = 0.22$ ). These two relationships might result from the fact that the separated HSR-air travel could provide more flexibility to passengers by allowing them to have more control over the travel themselves and shorten the waiting time between the major and minor leg, whereas the integrated counterpart might “force” those passengers to spend more time on waiting and use the integrated luggage handling service which is not required.

## B.2.2 Analysis II: posteriors from Bayesian estimation

### Method

Our next analysis obtains individual-specific posteriors from a Mixed Multinomial Logit (MMNL) analysis of the stated choice data and contrasts these with the B-W scores. Following the procedures proposed by Train (2009)<sup>1</sup> and Hess and Hensher (2010)<sup>2</sup>, we use Bayesian estimation of a MMNL model where we allow for random variation in all parameters, with correlation between individual parameters.

In the model specification, the utility that respondent  $n$  obtains from alternative  $i$  at choice task  $t$  is given as  $U_{int} = ASC_{in} + \beta'_n x_{int} + \varepsilon_{int}$ , with  $\beta_n$  being the vector of taste coefficients for respondent  $n$  and  $\varepsilon_{int}$  being iid extreme value. We constrain the coefficients for the alternative attributes to take the expected sign for all respondents by assuming positive Log-normal distribution for “good attributes” including delay protection, ticket integration and luggage integration ( $k = 4, 5, 6$ ), such that:

$$\beta_{nk} = e^{\mu_{ln}(\beta_{nk}) + \sigma_{nk}\xi_k} \quad (\text{B.1})$$

and negative Log-normal distribution for “bad attributes” including minor time, connection time, transfer time and travel cost ( $k = 1, 2, 3, 7$ ), in a form of:

$$\beta_{nk} = -e^{\mu_{ln}(-\beta_{nk}) + \sigma_{nk}\xi_k} \quad (\text{B.2})$$

where  $\mu$  and  $\sigma$  are the to-be-estimated means and standard deviations for the underlying Normal distribution.  $\xi_k$  follows a standard Normal distribution across respondents for attribute  $k$ , such that  $\xi_k \sim N(0, 1)$ .

The three alternative-specific constants (ASC) are specified to follow Normal distribution, to account for the underlying preference of the specific alternative which might be above or below the base alternative (i.e. integrated HSR-air is chosen as the base alternative as it has the lowest variance in an unidentified model<sup>3</sup>) given all else being equal. Minor time is separated between car or air and HSR; besides, different levels of some attributes, including delay protection, ticket integration, and luggage integration, are dummy coded with constraints that the utility sensitivity is monotonous for each attribute across the levels by

<sup>1</sup>Train, K.E., 2009. Discrete choice methods with simulation. Cambridge university press.

<sup>2</sup>Hess, S. and Hensher, D.A., 2010. Using conditioning on observed choices to retrieve individual-specific attribute processing strategies. Transportation Research Part B: Methodological, 44(6), pp.781-790.

<sup>3</sup>Walker, J.L., Ben-Akiva, M. and Bolduc, D., 2007. Identification of parameters in normal error component logit-mixture (NECLM) models. Journal of Applied Econometrics, 22(6), pp.1095-1125.

using additive Log-normal distributions to assure that higher level is better than the lower level for these attributes.

The models are estimated by using a panel formulation which assumes that sensitivities vary across respondents but stay constant across choice tasks for each respondent. The Bayesian estimation is conducted in RSGHB (Dumont et al., 2014)<sup>4</sup>, with 2,000,000 iterations in the burn-in procedure to use prior to convergence and another 200,000 iterations for averaging after convergence has been reached and we retain every fifth draw for averaging.

Let  $P_{nt}(i_{nt} | \beta_n)$  denote the conditional probability of respondent  $n$  choosing alternative  $i$  at choice task  $t$  given a specific value of  $\beta_n$ , which has a prior Normal density  $f(\beta_n | \theta)$  with  $\theta$  representing the collective of distributional parameters. We label the sequence of choices for respondent  $n$  as  $y_n$  and then the probability of observing  $y_n$  given  $\beta_n$  is denoted as  $P_n(y_n | \beta_n)$ . The marginal probability of observing  $y_n$  is given as the integral of the probability of the choice sequence conditional on  $\beta_n$  over the prior distribution of  $\beta_n$ , such that:

$$\begin{aligned} P_n(y_n) &= \int_{\beta_n} P_n(y_n | \beta_n) f(\beta_n | \theta) d\beta_n \\ &= \int_{\beta_n} \prod_{t=1}^T P_{nt}(i_{nt} | \beta_n) f(\beta_n | \theta) d\beta_n \end{aligned} \quad (\text{B.3})$$

Based on Bayes' rule, we can have the possibility of observing a specific value of  $\beta_n$  for respondent  $n$  given the observed choices  $y_n$  is:

$$P_n(\beta_n | y_n) = \frac{P_n(y_n | \beta_n) f(\beta_n | \theta)}{P_n(y_n)} \quad (\text{B.4})$$

which is also called posterior distribution. The mean of the posterior distribution for person  $n$ , which reflects the most likely value for the parameters given the observed choices for this person, is then given as:

$$\hat{\beta}_n = \frac{\sum_{r=1}^R [P(y_n | \beta_r) \beta_r]}{\sum_{r=1}^R P(y_n | \beta_r)} \quad (\text{B.5})$$

where  $\beta_r$  with  $r = 1, \dots, R$  are independent multi-dimensional draws with equal weight from  $f(\beta | \theta)$  at the estimated values for  $\theta$  (Hess, 2010)<sup>5</sup>.

## Results

Since posterior distributions are inferred from the SC data itself and B-W scores are information obtained from respondents' self assessment, we can thereby

<sup>4</sup>Dumont, J., Keller, J., Carpenter, C. and Dumont, M.J., 2014. Package 'RSGHB'.

<sup>5</sup>Hess, S., 2010. Conditional parameter estimates from mixed logit models: distributional assumptions and a free software tool. *Journal of Choice Modelling*, 3(2), pp.134-152.

bridge the understandings of attribute importance from these two different sides and also compare the inferred results with observed choice outcomes. We make use of the individual-specific mean of the posterior distribution for each attribute and analyse its correlation with the individual-specific B-W scores for each attribute, as shown in Fig. B.1, with the number in each cell giving the Pearson correlation between the corresponding row and column, where blue cells stand for positive correlations and red cells for negative correlations. For “good attributes”, the figure suggests positive correlations with the means of posterior distributions for almost all the sensitivity coefficients, in that higher B-W scores can be linked with more positive sensitivities of “good attributes”, and the converse applies for “bad attributes”. This means for example that if a respondent is observed to have higher B-W score on luggage integration, the mean of the posterior distribution for this coefficient is likely to be higher. We also see that there is positive correlation across the “good attributes”, indicating that someone who attaches high importance to some qualitative attributes is likely to do the same for others. The same rationale applies for “bad attributes”. This finding is also in accordance with our intuitive expectation that passengers who attach more importance to travel time or travel cost would be more restricted by the duration or the expenditure of the travel and meanwhile derive less positive utilities from those “good attributes”. For instance, those observed to have higher B-W scores on connection time are inferred to be more affected by the constraints on connection time or transfer time, and derive less positive utilities from the extra services provided by “good attributes”.

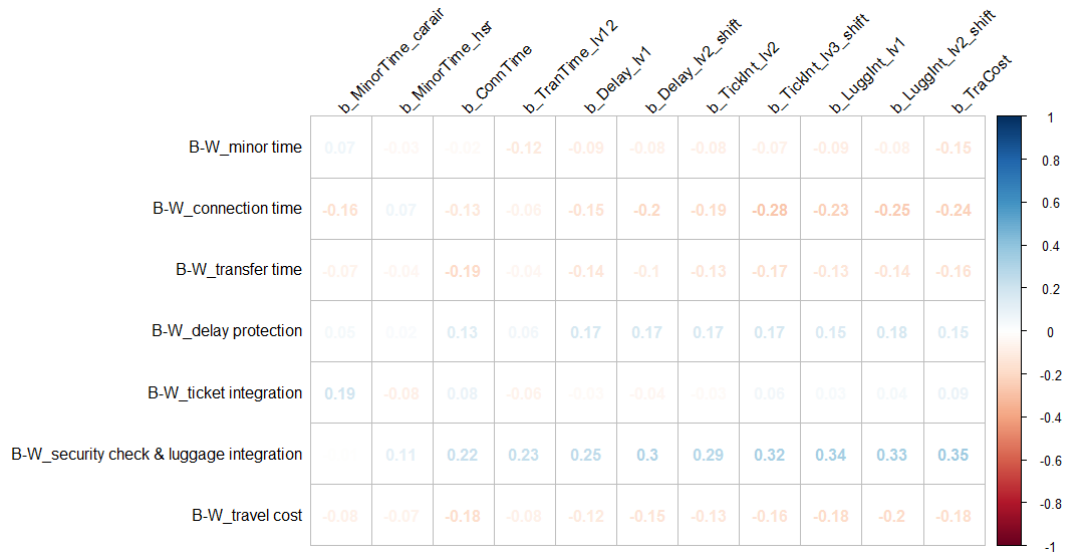
The presence of some weaker correlations between B-W scores and inferred sensitivity coefficients in Fig. B.1, like the results in our first analysis, suggests a probability of some inconsistency between passengers’ responses to B-W tasks and SC tasks for a subset of the attribute package, which might be the result of respondents rating attributes differently when not faced with a multi-alternative trade-off where they have to accept bad performance for some attributes in return for good performance for other.

### B.2.3 Analysis III: hybrid choice model approach

#### Method

We finally make use of a hybrid choice model based on the concept of latent attribute importance, which jointly explains taste heterogeneity in the choice model and the values of the B-W scores. This is analogous to the approach adopted in

## B.2. Initial analyses for the TRB paper



**Fig. B.1:** Correlation between B-W scores and posterior sensitivities.

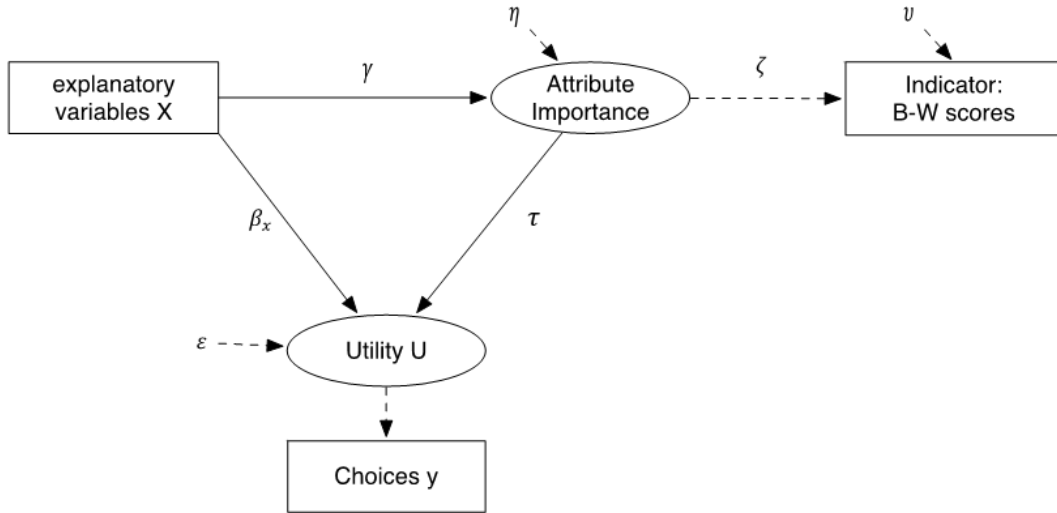
(Hess and Hensher, 2013)<sup>6</sup> and builds on the general hybrid framework<sup>7</sup> of (Ben-Akiva et al., 2002)<sup>8</sup>. Fig. B.2 provides an illustration of our model structure, where utilities are determined by both observable characteristics of alternatives and latent variables of attribute importance. The model consists of two parts, which are a choice model component and a latent variable component, each including structural equations and measurement equations. Items in rectangular are observable to researchers and items in ellipse are unobserved. Solid arrows represent structural equations which describe the causal relationship between unobserved items and observed items, while dashed arrows refer to measurement equations which explain indicators by latent variables or choices by utilities.

Since seven attributes are included in our survey, seven latent variables, each corresponding to a particular attribute, are defined here which are:  $\alpha_1$  for minor time,  $\alpha_2$  for connection time,  $\alpha_3$  for transfer time,  $\alpha_4$  for delay protection,  $\alpha_5$  for ticket integration,  $\alpha_6$  for luggage integration and  $\alpha_7$  for travel cost. The latent attribute importance is used to explain both the sensitivities to individual attributes in the utility function and the responses to indicators in the measurement equations, where the corresponding individual-specific B-W score is used as the indicator. In this exploratory work, we do not incorporate a deterministic

<sup>6</sup>Hess, S. and Hensher, D.A., 2013. Making use of respondent reported processing information to understand attribute importance: a latent variable scaling approach. *Transportation*, 40(2), pp.397-412.

<sup>7</sup>Hybrid choice model is also known as “Integrated choice and latent variable model”.

<sup>8</sup>Ben-Akiva, M., Walker, J., Bernardino, A.T., Gopinath, D.A., Morikawa, T. and Polypoulou, A., 2002. Integration of choice and latent variable models. *Perpetual motion: Travel behaviour research opportunities and application challenges*, pp.431-470.



**Fig. B.2:** Framework of the HCM model.

component into the structural equation, and thus assume pure randomness of the latent variable across respondents and specify Normal distribution for each latent variable, such that:

$$\alpha_{nk} = \eta_{nk} \quad (\text{B.6})$$

where  $\eta_{nk} \sim N(0, 1)$ .

We adopt a random coefficients formulation which allows for heterogeneous preference coefficients in addition to the impacts of latent variables across respondents, while maintaining homogeneity within a respondent across all choice tasks. Similar to Analysis II, Log-normal distributions are specified for all the attribute coefficients  $\beta_{nk}$  to assure the expected signs being taken by all respondents. Monotonic constraints are applied to the different levels of delay protection, ticket integration and luggage integration, where we allow for different means for the underlying Normals but due to limited data rely on the same variance of the underlying Normal distribution for different levels of  $k$ . Correlations are not specified between different underlying Normal distribution for the same reason. We specify an exponential multiplier for attribute importance, such that the separate random utility coefficient for attribute  $k$  is multiplied by  $e^{\tau_k \alpha_{nk}}$ , where  $\tau_k$  measures the impact of latent  $\alpha_{nk}$  on scaling the sensitivity coefficients  $\beta_{nk}$  inside the choice model. As the latent variable has a Normal error term (see Eq. (B.6)), the scaled sensitivity coefficients still follow a Log-normal distribution.

## B.2. Initial analyses for the TRB paper

We then have:

$$\begin{aligned}
\beta_{n1,ca} &= -e^{\tau_1\alpha_1} e^{\mu_{ln(-\beta_{n1,ca})} + \sigma_1\xi_1} \\
\beta_{n1,h} &= -e^{\tau_1\alpha_1} e^{\mu_{ln(-\beta_{n1,h})} + \sigma_1\xi_1} \\
\beta_{n2} &= -e^{\tau_2\alpha_2} e^{\mu_{ln(-\beta_{n2})} + \sigma_2\xi_2} \\
\beta_{n3} &= -e^{\tau_3\alpha_3} e^{\mu_{ln(-\beta_{n3})} + \sigma_3\xi_3} \\
\beta_{n4,1} &= e^{\tau_4\alpha_4} e^{\mu_{ln(\beta_{n4,1})} + \sigma_4\xi_4} \\
\beta_{n4,2\_shift} &= \beta_{n4,1} + e^{\tau_4\alpha_4} e^{\mu_{ln(\beta_{n4,2\_shift})} + \sigma_4\xi_4} \\
\beta_{n5,2} &= e^{\tau_5\alpha_5} e^{\mu_{ln(\beta_{n5,2})} + \sigma_5\xi_5} \\
\beta_{n5,3\_shift} &= \beta_{n5,2} + e^{\tau_5\alpha_5} e^{\mu_{ln(\beta_{n5,3\_shift})} + \sigma_5\xi_5} \\
\beta_{n6,1} &= e^{\tau_6\alpha_6} e^{\mu_{ln(\beta_{n6,1})} + \sigma_6\xi_6} \\
\beta_{n6,2\_shift} &= \beta_{n6,1} + e^{\tau_6\alpha_6} e^{\mu_{ln(\beta_{n6,2\_shift})} + \sigma_6\xi_6} \\
\beta_{n7} &= -e^{\tau_7\alpha_7} e^{\mu_{ln(-\beta_{n7})} + \sigma_7\xi_7}
\end{aligned} \tag{B.7}$$

where the subscript  $k$  after  $n$  stands for the attribute (i.e, minor time:  $k = 1$ , connection time:  $k = 2$ , transfer time:  $k = 3$ , delay protection:  $k = 4$ , ticket integration:  $k = 5$ , luggage integration:  $k = 6$ , travel cost:  $k = 7$ ). The subscript after the comma in  $\beta_{n4}$ ,  $\beta_{n5}$ , and  $\beta_{n6}$  relates to different levels of the attribute, while in  $\beta_{n1}$ , it stands for the separate estimates for car or air and for HSR.

In the measurement equations, the individual-specific B-W scores  $I_{nk}$  are treated as indicators of the corresponding latent variable  $\alpha_k$  and each indicator requires a separate measurement equation. Although ordered Logit specifications in measurement equation (Daly et al., 2012)<sup>9</sup> have been advocated in recent years to account for the ordered nature of responses to attitudinal statements, we still adopt the traditional linear specification as our B-W scores are not responses on a Likert scale and may range from -4 to 4, such that a large number of parameters would need to be estimated with sparse data. The measurement equations can thus be modelled as:

$$I_{nk} = \zeta_k \alpha_{nk} + v_{nk} \tag{B.8}$$

where  $\zeta$  are the to-be-estimated parameters that reflect the impacts of latent variables on B-W score indicators. The random term  $v_{nk}$  is assumed to follow a Normal distribution with a mean of zero, such that  $v_{nk} \sim N(0, \varsigma)$  with  $\varsigma$  being the standard deviation to be estimated.

---

<sup>9</sup>Daly, A., Hess, S., Patruni, B., Potoglou, D. and Rohr, C., 2012. Using ordered attitudinal indicators in a latent variable choice model: a study of the impact of security on rail travel behaviour. *Transportation*, 39(2), pp.267-297.

Log-likelihood maximisation is adopted for estimation, such that  $\max(LL(Y, I))$ , where we need to maximise the log-likelihood of observing the choices  $Y$  and indicators  $I$ . The unconditional probability of observing choices  $Y$  and indicators  $I$  can be expressed as the integral of the multiplication of conditional choice probability and the conditional indicator probability over the distribution of the latent variables, such that:

$$LL(Y, I) = \sum_{n=1}^N \ln \int_{\beta_n^*} \int_{\alpha_n} \left( \prod_{t=1}^{T_n} P(y_{nt} | \beta_{nt}^*, \alpha_n) \right) \times \left( \prod_{k=1}^{K_n} P(I_{nk} | \alpha_n) \right) f(\alpha_n) d\alpha_n f(\beta_n^* | \theta) d\beta_n^* \quad (\text{B.9})$$

As random coefficients are accounted for within a panel formulation, a second layer of integral over all possible values of  $\beta$  is required. Since the resulting  $LL$  does not have closed-form expression, the estimation needs to be approximated through simulation. The presence of the separate layer of random heterogeneity ensures that we do not misattribute heterogeneity to the latent variables but are able to disentangle a random part which is linked to the latent variable and a part which is not (i.e.  $\beta_n^*$  represents the random part in  $\beta_n$  that is irrelevant from the latent variable).

### Estimation results

The estimation results of the hybrid choice model are presented in Table B.2, where items with  $|t\text{-rat.}| \geq 1.96$  are significant at 95% confidence level. The significant estimates of the three alternative specific constants suggest the existence of underlying preference for these alternatives, where we do not in the present work allow for additional heterogeneity in these constants.

We first look at the estimates for the measurement equations before turning to the impact of the latent variables on scaling utility sensitivities in the choice model component. It is shown that  $\zeta_4$ ,  $\zeta_5$ ,  $\zeta_6$ , and  $\zeta_7$  are significant at 95% confidence level and  $\zeta_2$  is significant at 85% level, which suggests that the indicators of B-W scores for attributes of delay protection, ticket integration, luggage integration and travel cost and potentially connection time are significantly affected by the corresponding latent variables. The positive signs for  $\zeta_2$ ,  $\zeta_4$ ,  $\zeta_6$ , and  $\zeta_7$  and negative sign for  $\zeta_5$  show that stronger latent  $\alpha_2$ ,  $\alpha_4$ ,  $\alpha_6$ ,  $\alpha_7$  and weaker  $\alpha_5$  would lead to an increase in the corresponding B-W score. This also suggests that  $\alpha_2$ ,  $\alpha_4$ ,  $\alpha_6$ ,  $\alpha_7$  actually stands for ‘‘attribute importance’’ of connection time, delay protection, luggage integration and travel cost respectively, while  $\alpha_5$  for ‘‘attribute unimportance’’ of ticket integration. On the contrary, the impacts for latent variables  $\alpha_1$  and  $\alpha_3$  on the corresponding B-W score indicators are not



clear ( $\zeta_1$ :  $t$ -rat.= $-0.11$ ,  $\zeta_3$ :  $t$ -rat.= $0.49$ ). Since minor time has the lowest aggregated B-W counts and transfer time has the lowest standard deviation of B-W scores (see Table 4.1), it may suggest that the majority of respondents view minor time as very unimportant in decision making and have the least difference in the opinions on transfer time, which could potentially result in the insignificant impacts of latent attribute importance on the B-W scores.

Turning to the impacts of latent variables in the choice model, it is shown that  $\tau$  are significantly estimated for all the attributes except for ticket integration ( $\tau_5$ :  $t$ -rat.= $-0.43$ ), revealing the presence of scaling effect introduced by latent variables on attribute importance, which confirms the findings in previous research (Hess and Hensher, 2013). The negative sign for minor time ( $\tau_1$ ) and the positive signs for the remains imply that a decrease in latent variable  $\alpha_1$  and increases in the latent variable  $\alpha_2$ ,  $\alpha_3$ ,  $\alpha_4$ ,  $\alpha_6$  and  $\alpha_7$  can lead to stronger utility sensitivities for the attribute concerned. Such results are generally in accordance with our expectations, as earlier interpretation of  $\alpha_2$ ,  $\alpha_4$ ,  $\alpha_6$  and  $\alpha_7$  as “attribute importance” shows that stronger attribute importance attached to connection time, delay protection, luggage integration and travel cost leads to stronger scaling effect and thus higher marginal utilities on concerned attribute, while weaker attribute importance results in a higher possibility that the concerned attribute is ignored or ranked as less important. In addition, though the corresponding impacts of latent variables on B-W indicators are not significantly estimated in respect of minor time and transfer time (see  $\zeta_1$  and  $\zeta_3$ ), the significant  $\tau_1$  and  $\tau_3$  together with the significant corresponding variances  $\varsigma_1$  and  $\varsigma_3$  still manifest the presence of scaling effect for the attributes of minor time and transfer time, which is purely random and irrelevant to the latent variable, making it difficult to define what latent constructs  $\alpha_1$  and  $\alpha_3$  actually stand for.

Turning to the estimates of the underlying Normal distributions for the utility sensitivity coefficients, all the underlying means except for  $\mu_{\ln(-\beta_{tick3\_shift})}$  and all the underlying variances except for  $\sigma_5$  are significant at 90% level at least, suggesting the presence of random heterogeneity independent of the latent variables. In addition to the random heterogeneity in the  $\beta$  parameters, we also see an impact by the latent variable through the  $\tau$  parameter. These need to be interpreted alongside the  $\zeta$  parameters. We can observe that for delay protection, luggage integration and travel cost, increases in the latent variable lead to higher B-W scores as well as increases in the absolute value of  $\beta$ , supporting a link between attribute importance in the SC data and the B-W scores. A weaker link exists for connection time, where the  $\zeta$  term is only marginally significant but  $\tau$  is highly significant.

**Table B.2:** Estimation results of the joint model

Parameter#	42				
Respondent#	123				
Observation#	984				
$LL(0)$	whole model: -4227.743				
$LL(\text{final})$	whole model: -2897.1490				
	choice component: -1033.7510				
adj. $\rho^2$	whole model: 0.3091				
$AIC$	whole model: 5878.3				
$BIC$	whole model: 6083.75				
Choice model	est.	$t$ -rat.	Measurement equation	est.	$t$ -rat.
$ASC_1$	-1.9184	-3.32	$\zeta_1$	-0.0497	-0.11
$ASC_2$	0.9605	4.37	$\zeta_2$	0.3881	1.46
$ASC_3$	-0.9467	-4.26	$\zeta_3$	0.1824	0.49
$\mu_{\ln(-\beta_{MT\_ca})}$	-4.4591	-14.28	$\zeta_4$	1.2100	2.38
$\mu_{\ln(-\beta_{MT\_h})}$	-6.2729	-12.71	$\zeta_5$	-1.2910	-3.63
$\mu_{\ln(-\beta_{CT})}$	-4.4440	-35.22	$\zeta_6$	1.5603	4.38
$\mu_{\ln(-\beta_{TT})}$	-0.4295	-1.68	$\zeta_7$	0.7466	2.09
$\mu_{\ln(\beta_{delay1})}$	-1.8489	-1.91	$\varsigma_1$	1.7727	17.36
$\mu_{\ln(\beta_{delay2\_shift})}$	-2.6082	-1.65	$\varsigma_2$	1.9553	17.34
$\mu_{\ln(\beta_{tick2})}$	-10.5726	-1.69	$\varsigma_3$	1.7513	14.39
$\mu_{\ln(\beta_{tick3\_shift})}$	-10.6946	-1.07	$\varsigma_4$	1.9880	6.16
$\mu_{\ln(\beta_{lugg1})}$	-0.8108	-2.33	$\varsigma_5$	1.8827	8.91
$\mu_{\ln(\beta_{lugg2\_shift})}$	-4.6191	-1.49	$\varsigma_6$	2.0626	7.99
$\mu_{\ln(-\beta_{TC})}$	-6.0995	-28.61	$\varsigma_7$	2.3746	16.81
$\sigma_1$	-1.0760	-5.23			
$\sigma_2$	0.2381	3.95			
$\sigma_3$	0.4422	2.34			
$\sigma_4$	-0.4678	-3.43			
$\sigma_5$	-0.9768	-0.54			
$\sigma_6$	-0.7076	-5.25			
$\sigma_7$	0.4660	1.74			
$\tau_1$	-0.6332	-5.02			
$\tau_2$	0.5496	6.76			
$\tau_3$	0.6741	6.27			
$\tau_4$	1.0866	4.59			
$\tau_5$	-1.8921	-0.43			
$\tau_6$	1.2029	5.45			
$\tau_7$	0.5023	4.73			