An Integrated Choice and Latent Variable Model to Explore the Influence of Attitudinal and Perceptual Factors on Shared Mobility Choices and Their Value of Time Estimation

Weibo Li, Corresponding Author

University College London

UCL Energy Institute, Central House, 14 Upper Woburn Place, WC1H 0NN, London, UK

Email: weibo.li.10@ucl.ac.uk

Maria Kamargianni

University College London

UCL Energy Institute, Central House, 14 Upper Woburn Place, WC1H 0NN, London, UK

Email: m.kamargianni@ucl.ac.uk

ABSTRACT

This work studies how the usage of shared mobility services could be influenced by latent factors. An integrated choice and latent variable (ICLV) model is adopted to explore the effects of three attitudinal and perceptual factors on bike-sharing and car-sharing choices while simultaneously investigating the causes associated with each of the latent variables. A group of Chinese commuters' stated preference mode choice data is collected. It is found that the probability to choose bike-sharing could be positively affected by "Willingness to be a green traveler" and "Satisfaction with cycling environment"; while car-sharing choice is positively correlated with "Advocacy of car-sharing service". By taking into account the interaction effects between the latent variables and travel time of the two services, significant difference is discovered on the estimated value of travel time savings (VTTS) comparing to other more restrictive model specifications. The finding highlights the importance to derive different VTTS for travelers with differentiated attitudes and perceptions, as the tastes towards travel time spent could vary substantially. In other words, there would be different trade-off preferences across attitudinal groups, according to which transport service operators could customize their strategies on prices and levels of service offered.

Keywords: Bike-sharing; Car-sharing; Commute mode choice; Attitude and perception; Taste heterogeneity; Value of time

1. INTRODUCTION

Shared mobility services, in particular bike-sharing and car-sharing, have attracted tremendous amount of research attention in the last couple of years. On the demand side, many mode choice studies were conducted in order to find evidence and offer guidance to relevant policy making. So far, a variety of factors (e.g. socio-economic characteristics, trip and mode attributes, built and natural environmental conditions etc.) have been studied with regard to their impacts on the decisions to use bike-sharing and car-sharing for daily trips; a review of those works and findings is referred to Li and Kamargianni (2018, 2019). Nevertheless, there could be further opportunities to enhance the behavioral realism of shared mobility choices and one potential path is via exploring the influence of latent variables (i.e. attitudes and perceptions) on mode choice decisions.

The research in such a dimension has substantial benefits, i.e. explicitly modeling unobserved heterogeneity, increasing estimation efficiency and goodness-of-fit, enhancing behavioral realism, and extending policy relevance (Abou-Zeid and Ben-Akiva, 2014), and has already been found on various mode choice related topics. For instance, Johansson et al. (2006) took into account travelers' attitudes towards a number of issues, such as environment, safety, comfort, convenience and flexibility, to help explain the choice behavior towards car and public transport. Paulssen et al. (2014) studied a similar set of mode choices and attitudes, and they even further brought in and analyzed the impacts of personal values (i.e. the factors that "lie at the heart of an individual's belief system") on both mode choices and attitudes. Apart from car and public transport, Sarkar and Mallikarjuna (2018) discovered also the significance of flexibility perception in affecting the demand for two and three wheeled motorcycles. Kamargianni et al. (2015) found that the mode choices when traveling to school could be influenced by teenagers' attitudes towards safety, green lifestyle and physical activity. There were also direct comparisons on model performance where mode choice models by adding in latent attitudes and perceptions always outperformed the corresponding base models in terms of predictive power (Yanez et al., 2010; Chen and Li, 2017). In addition, some similar practices can be found in Bolduc et al. (2008), Daziano and Bolduc (2013), Kim et al. (2014), Beck et al. (2017) and Smith et al. (2017) on vehicle type choices (i.e. usually involving electric vehicle), Belgiawan et al. (2017) on student's car purchase decision, Fleischer et al. (2012) on flight choice and Song et al. (2018) on high-speed rail choice.

Although, to our knowledge, bike-sharing choice has rarely been evaluated through latent variable influence, there are works trying to reveal how such factors might affect general cycling choice. Pro-bike attitudes, which could include general willingness to cycle and consciousness towards environment and sustainability issues, were popular factors that have been analyzed in many studies and were often identified as important driving forces to cycling usage (Kamargianni and Polydoropoulou, 2013; Maldonado-Hinarejos et al., 2014; Fernandez-Heredia et al., 2016). Similarly, the feelings towards internal (e.g. personal fitness) and external (e.g. weather and topography etc.) conditions could also heavily affect a traveler's decision to cycle, as being identified in several cases (La Paix Puello and Geurs, 2015; Motoaki and Daziano, 2015; Fernandez-Heredia et al., 2016). Nonetheless, these mostly studied attitudes and perceptions may sometimes be less important according to the results of a Spanish case study by Munoz et al. (2016), in which the authors found the impacts of pro-bike lifestyles, environmental awareness and the perceptions on cycling capability were rather insignificant. Finally, some other latent factors have also been examined in the aforementioned cycling choice studies, such as the perceptions of convenience and comfort, safety concerns and social norms, which could influence cycling choice as well to some extent.

With respect to car-sharing choice, only few recent studies have started to explore the potential influence of latent factors. Efthymiou and Antoniou (2016) and Kim et al. (2017a) identified in both of their works that the intention to join a car-sharing scheme could be significantly affected by people's satisfaction with their current travel patterns and habits. Kim et al. (2017b) discovered further that car-sharing choice was highly associated with pro-environmental and privacy-seeking attitudes, and perceptions on the symbolic value of cars. In the work by Vinayak et al. (2018), the frequency of using car-sharing was not only affected by attitudes such as pro-environmental and neo-urban lifestyle preferences, but also by socio-interactions (i.e. someone's behavior depends on the behaviors of those in close proximity). Additionally, Correia et al. (2010) looked at carpooling and found such a mode choice could be heavily affected by people's positive/negative attitudes and familiarity with the service.

Besides the relatively limited understanding of how shared mobility choices might be influenced by personal attitudes and perceptions, another matter that could contribute to travel demand management but yet rarely looked at is the estimation of value of travel time savings (VTTS) under the presence of latent factors. To our knowledge, Abou-Zeid et al. (2010) for the first time studied the interaction effects between latent factors and travel time or cost in order to have a more accurate calculation for VTTS. This is due to people with different attitudes and perceptions could have different valuations towards trip-related factors and thus the willingness to pay for travel time savings could also be different. In other words, VTTS will no longer be identical across the population and need to be integrated over all individuals to derive a value at the societal level. Nevertheless, we noticed from the results of Abou-Zeid et al. (2010) that there is only a small difference (around 7%) between the VTTS estimated from a base mode choice model and from an integrated choice and latent variable (ICLV) mode choice model which captures an attitudinal factor's interaction with travel cost. Such amount of difference is significantly smaller than a few earlier results when the impact of systematic and random taste heterogeneity on value of time was studied (Algers et al., 1998; Hensher, 2001a; Amador et al., 2005). In fact, the three works here all discovered around 40% difference when comparing the VTTS estimated from a base MNL model and from an ML model that captures taste heterogeneity. Algers et al. (1998) found the more flexible ML model decreased VTTS, while the other two (Hensher, 2001a; Amador et al., 2005) found the results in a completely opposite way (in another study, Alpizar and Carlsson (2003) argued value of time could either increase or decrease with a more flexible model specification depending on the chosen mode). Now a question may pop up that if the much smaller difference revealed by Abou-Zeid et al. (2010) would imply the non-significant influence of personal attitudes in VTTS estimation or there could be other explanations behind. As a result, we looked into their study and found from the survey statistics that 3 out of the 4 modeled indicators which reflect people's attitude towards car use were highly skewed in one direction, which strongly suggests the sampled individuals were sharing close rather than differentiated attitudes. Thus, it may be able to explain why capturing taste heterogeneity contributed so little to VTTS estimation (because there is no significant taste heterogeneity), though this hypothesis should be further tested. Unfortunately, to date, no other evidence was found apart from Bahamonde-Birke et al. (2017), which noticed as well the opportunity to calculate VTTS after seeing the interactions between attitudes and travel time, though no empirical results were provided in the study.

Thus, in our subsequent analysis, we are not only aiming to enrich the literature by revealing how several types of attitudes and perceptions could possibly affect bike-sharing and car-sharing choices, but also trying to investigate the extent to which VTTS estimation for shared mobility could be affected by the presence of these latent factors, especially when the interaction with travel time or cost is captured, and hence offering more evidence to the subject. However, it is noteworthy that any potential result (e.g. to what extent VTTS may be affected) is not meant to be straight comparable to the values found in Algers et al. (1998), Hensher (2001a), Amador et al. (2005), or even Abou-Zeid et al. (2010), and based on which draw deterministic conclusions. This is because some natural differences between studies, such as variables used to specify the model and any unaccounted local characteristics of the case study sample, could all lead to different values being obtained.

The case study of this research is Taiyuan, China. A survey was launched to collect local citizens' stated preference (SP) mode choice data as well as their attitudinal and perceptual information. This research analyzes the data collected from 3,486 individuals and their 6,381 SP commute trip observations. We are particularly interested in studying commute mode choices since such effort is needed the most for many Chinese major cities, to help increase shared mobility usage for morning peak-hour traffic. Three latent factors are revealed from the survey results, and they are "Willingness to be a green traveler", "Satisfaction with cycling environment" and "Advocacy of car-sharing service".

Attitudinal and perceptual information is usually analyzed through an ICLV model in today's mode choice studies (Ben-Akiva et al., 2002; Walker and Ben-Akiva, 2002; Bolduc et al., 2005; Bolduc and Alvarez-Daziano, 2010); though being less preferred, some other methods proposed in earlier days are also available to use (see Bhat and Dubey (2014) for a review). In general, the ICLV model provides an integrated modeling framework which consists of a latent variable model and a discrete choice model. The latent variable model studies the potential causes of latent variables via a structural equation system and also analyzes via a set of measurement equations the observed indicators through which latent variables are manifested. The discrete choice model evaluates mode choice utilities as usual but now taking into account the impacts of latent variables as well alongside other explanatory factors. Our research follows such an ICLV modeling framework, with a nested logit structure developed for the discrete choice sub-model.

Through a robust integrated modeling analysis, the impacts of latent factors on bike-sharing and car-sharing choices can be quantitatively revealed, to provide better understanding of shared mobility choice behavior. Policy implications may also be acquired in terms of the potential to promote shared mobility usage via affecting people's attitudes and perceptions. The value of time analysis will disclose how much difference the latent variables could make on VTTS estimates; in other words, this will tell whether different VTTS estimates are needed for travelers with differentiated attitudes and perceptions. Besides, studying bike-sharing and car-sharing choice behavior in China could be particularly valuable in this era given the fast expansion of sharing economy in this country.

The work is structured as follows. Section 2 describes in detail the sample data that will be analyzed in the ICLV model. Section 3 explains the modeling framework and section 4 evaluates the model estimation results. Finally, section 5 concludes the paper.

2. MODE CHOICE DATA AND LATENT FACTORS

A paper-based questionnaire survey was conducted in summer 2015 at Taiyuan, China. The city has more than 3 million people and has been making constant progress towards a future with less dependence on private car and fossil fuel. In 2012, Taiyuan participated as one of the first few member cities in China's "Transit Metropolis" project (Jiang et al., 2013); at the same year, a publicly operated bike-sharing scheme was launched and has become one of the most in demand schemes in the country (Burkholder, 2015; Hiles, 2015); in 2016, Taiyuan undertook an extensive taxi overhaul project by replacing all of its taxi fleets with electric vehicles (Global Opportunity Explorer, 2016); finally since 2017, several EV car-sharing pilot schemes entered the city and were expected to grow rapidly in near future due to the strong nationwide interest on such a type of service (Hao, 2017; Xinhua, 2017).

The survey aimed to capture Taiyuan citizens' mode choice behavior on shared mobility services, as well as their socio-economic characteristics and personal attitudes & perceptions on various transportation-related issues. Specifically, we designed an SP experiment to gather the mode choice information as this offers a way to capture the choice of car-sharing, while the service was not available in the city of Taiyuan at the time of the survey (and even now the public still have no wide access to the service as only few pilot schemes exist). There were seven alternative modes included in the choice set: 1.

Bike-sharing, 2. Car-sharing, 3. Bus, 4. Taxi, 5. Walk, 6. Electric bike, and 7. Car, as we would like to capture all the urban transport options that are frequently used by Taiyuan citizens (though, except car-sharing), with the private bike being excluded due to its continuously decreasing usage as a result of the continuous expansion of the city's bike-sharing program. Table 1 gives an overview of the SP survey design. Each of the aforementioned alternatives possessed several mode-specific attributes, with trip distance, trip purpose, temperature, weather and air pollution as the external conditions. Attributes of the modes and their levels were generated in light of our pilot survey results (with around 150 participants), the settings adopted by previous SP mode choice research, and the advices from local experts in the city of Taiyuan. The SP survey adopted the traditional orthogonal (main effects) design, with a blocking design followed to limit the number of SP scenarios presented in a questionnaire (Louviere et al., 2003). The software we used is SPSS, which could ensure the process of scenario generation preserves orthogonality, provided the required degree of freedom (DoF) is obtained (Hensher et al., 2005). More details regarding the DoF calculation and the blocked design for our survey are referred to Li (2019). Eventually, each respondent was asked to make mode choices in six scenarios.

TABLE 1 An Overview of the Design of the SP Mode Choice Experiment

Trip distance: within 2km, between 2km and 5km, more than 5km
Trip purpose: commute, leisure, shopping.
Weather: sunny (-10°, -5°, 0°, 5°, 10°, 20°, 25°, 30°), snow (-10°, -5°, 0°), rain (5°, 10°, 20°, 25°, 30°).
Air pollution level: excellent, good, light pollution, medium pollution, heavy pollution, terrible pollution.

	Bike-sharing	**Car-sharing**	**Bus**	**Taxi**	**Walk**	**Electric bike**	**Car**
Travel time	8, …, 120 min (12 levels)	2, …, 40 min (10 levels)	5, …, 60 min (11 levels)	5, …, 40 min (7 levels)	10, …, 30 min (5 levels)	5, …, 60 min (13 levels)	2, …, 40 min (10 levels)
Travel cost*	￥0, …, 3 (6 levels)	￥0.8, …, 40 (14 levels)	￥0.5, …, 2.5 (5 levels)	￥10, …, 50 (9 levels)			￥1, …, 20 (17 levels)
Parking space							Easy/hard to find parking
Parking cost*							Free, ￥2/h, ￥5/h, ￥8/h.
Walking time to/from station	2min, 5min, 10min.	5min, 10min, 15min.	5min, 10min, 15min.				
Bus Frequency			Every 2min, 5min, 10min, 15min.				

Mobile app availability	Yes, no.	Yes, no.	Yes, no.	Yes, no.

1. For the measurement of air pollution, the six levels used here are the official terms reported to the public on a daily base and they are derived from a quantitative measure (i.e. the air quality index (AQI), details of which are presented in Table 3 when specifying how air pollution is measured in the models).
2. For each mode, there are many levels introduced for travel time and travel cost. This enables the SP design to select from different set of available values when scenarios vary between the three trip-distance cases (see more details in Li, 2019).
3. To customize the scenarios with the current travel pattern in Taiyuan, we made "taxi" an unavailable option in the choice set when a scenario has trip distance "within 2km"; likewise, "walk" is made unavailable when a scenario has trip distance "between 2km and 5km" or "more than 5km".

* ￥1 ≈ $0.15

The way that attitudes and perceptions were captured was presenting in the questionnaire a list of statements and the respondents were asked to indicate to what extent they would agree with each of the statements. These statements belonged to four subjects: general environmental consciousness, attitudes and perceptions on public transport, bike-sharing and car-sharing. The degrees of agreement were measured using a 7-point Likert-scale (Likert, 1932) where: 1. Completely disagree; 2. Strongly disagree; 3. Disagree; 4. Neutral; 5. Agree; 6. Strongly agree and 7. Completely agree.

To collect the data, we distributed the questionnaire to 15,000 Taiyuan citizens over the summer months of 2015. Due to the population size of more than 3 million in the urban area of Taiyuan, we employed a 2-stage stratified sampling technique to calibrate our sample in light of the city's census data. Specifically, for the first stage, the sampled individuals were proportionally spread over the six administrative districts in the urban area as per the population size in each district; and then, for the second stage, the gender distribution of sampled individuals in each district was set to be proportional to the population gender distribution in each district. We co-operated with Shanxi Transportation Research Institute, which provided fifteen researchers assisting with the questionnaire distribution, questionnaire collection and incorporation of the data into electronic datasets.

Moreover, given the large number of 15,000 respondents and the relatively lengthy time we estimated for completing a questionnaire (around 20 minutes in average), instead of randomly capturing people on streets, the fifteen researchers were sent to liaise with communities, enterprises, organization from public sectors as well as universities and other educational institutions to search for survey participants. This approach allowed us to effectively assemble the required number of individuals; meanwhile, we found over 40 liaised partners for questionnaire dissemination to try to retain the diversity of socio-economic characteristics among the sampled respondents.

After the collection of questionnaires, the data cleaning reduced the sample size to around 9,000 individuals, who provided their corresponding mode choice information (i.e. after removing missing, invalid and extreme values). However, as this research is more interested in commute trips and attitudinal & perceptual information, the sample was further filtered by keeping only those SP observations where the trip purpose is commute and those individuals who responded to the questions about attitudes & perceptions and in a valid manner (i.e. a tolerance threshold is applied on the number of patterned scores given to consecutive statements and if the scores have significant inconsistency among several comparable statements). Eventually, the final dataset for this research includes 3,486 individuals with 6,381 SP mode choice observations.

However, it should be noticed that a further selection of the data based on trip purpose would compromise orthogonality of the SP experimental design. In other words, correlations among the attributes may arise, and a test for multicollinearity would be required (Hensher et al., 2005). We relied on the commonly used Pearson's pairwise correlation coefficient (with a threshold of 0.8) to test if the correlation in any possible attribute pairs from the SP survey (see Table 1) could be high enough to cause problems for model estimation. Fortunately, only a single pair (taxi travel time and taxi travel cost) among those many combinations slightly exceeded the limit (0.829 in robust measure), which may not significantly affect the mode choice analysis later on given our focus on bike-sharing and car-sharing in this case.

Table 2 presents the key descriptive statistics of the final sample and the mode choices in the labeled SP survey. The commuters mainly consist of those aged between 26 and 45 (83%), and most of them are married (85%). Gender and educational level distributions are relatively equal where the number of males and females are close and a half of the sample has a university degree. There is a high possession rate of public transport card (87%) meaning that most of the commuters can access bus and bike-sharing services “barrier-free”. Finally, more than 60% of the respondents have a driving license and almost all respondents have good health status to cycle (96%).

TABLE 2 Sample Descriptive Statistics

		N=3,486
Gender	Male	54%
	Female	46%
Age	under 18	-
	18-25	1%
	26-35	48%
	36-45	35%
	46-59	15%
	60 or above	1%
Marital status	Single	15%
	Married	85%
Educational level	High school or below	22%
	College	29%
	Undergraduate	41%
	Graduate and above	8%
Driving license	Percentage of possession	64%
Public transport card	Percentage of possession	87%
Cycling capability	Healthy enough to cycle	96%
Household monthly income (after tax)*	Under ￥3000	21%
	￥3000 -￥6000	42%
	￥6000 -￥9000	23%
	￥9000 -￥15000	10%
	￥15000 -￥30000	3%
	Over ￥30000	1%
Household car	Percentage of possession	56%
Household electric bike	Percentage of possession	44%
Household bike	Percentage of possession	31%

Commute Trip Modal Splits (6,381 SP obs.)						
Bike-sharing	Car-sharing	Bus	Taxi	Walk	Electric bike	Car
11%	14%	27%	4%	12%	10%	22%

The latent construct of our ICLV model was determined using the collected attitudinal and perceptual information. To reveal the potential latent variables and the best indicators through which the latent variables are manifested, a principal component analysis (Jolliffe, 2002) was conducted followed by a varimax rotation (Kaiser, 1958) to assess the factor loadings of all possibly relevant statements in the survey. Eventually, three latent variables came out with sufficient number of supportive statements. Based on the information carried by the statements, we named the three latent variables as: “Willingness to be a green traveler” with five statements as its indicators, “Satisfaction with cycling environment” with four statements and “Advocacy of car-sharing service” with four statements. Their statistics are given in Fig. 1, 2 and 3 respectively, displaying the percentages of the sampled individuals agreeing/disagreeing with different levels.

In Fig. 1, the detected five statements actually coincide with Taiyuan municipality’s aforementioned movement towards an eco-friendly transport system. In general, the sampled respondents seem to be supportive to such a vision by having more than 60% positive responses (i.e. “Agree”, “Strongly agree” or “Completely agree”) in all five statements. The details, however, do differentiate slightly. By comparing across the first three statements, we can see even if people are willing to use low-carbon transport for themselves and even persuade others, they could be less willing to sacrifice their private car usage. Similarly, when mentioning the word “policy” even if in general (the 4th statement), people tend to be more conservative in terms of releasing positive responses.

In Fig. 2, the first two statements reflect the city’s bike-sharing service standards with respect to price and station distance. The results show that commuters are mostly satisfied with the current price scheme by having nearly 40% of them completely agree with the statement “I am satisfied with the current bike-sharing price” and less than 20% expressed negative responses (i.e. “Disagree”, “Strongly disagree” or “Completely disagree”). Unlike many cities in the world, the charging scheme that Taiyuan bike-sharing operator (Taiyuan Public Transport Holdings) adopts does not require a fixed/access fee each time. Users only need to pay based on the amount of time they spend (i.e. free in the first hour, ￥1/h for the next hour, ￥2/h for the next and ￥3/h for the rest of day). Moreover, a user can return the bike to a docking station and get replaced with another one instantly to re-start the time count and avoid being charged. As for station distance, the current average distance between any two stations is smaller than 500 meters (Toutiao, 2017).

The latter two statements in Fig. 2 reflect the indirect issues that bike-sharing users may consider. Firstly, the current traffic rules in Taiyuan have both pros and cons to cyclists. On the one hand, unlike the strict rules and punishments that car drivers have to bear, cyclists can travel much more freely. On the other hand, however, there are no individual green lights for "going straight" and "turning right" (vehicles travel on the right side in China). Hence, bicycles which go straight could have direct conflict with cars which turn right. Studies have also shown that cyclists could have great safety concerns if cars were closely aside (Fishman et al., 2012; Paschalidis et al., 2016; Piatkowski et al., 2017; Romero et al., 2017). Secondly, perceptions on public security may also affect bike-sharing usage due to the fear of crime or the perceived sense of being unsafe could discourage travelers from using non-private modes (McCarthy et al., 2016). Nevertheless, it seems that Taiyuan municipality has created a generally satisfactory cycling environment since more than 60% of the sampled individuals give positive responses to both traffic rule and public security statements, as well as to the two statements on service standards.

Finally, Fig. 3 illustrates an overall optimistic view on car-sharing service and its future. However, by comparing between "Car-sharing could make me reduce private car usage" and "Car-sharing could make me reconsider whether or not to purchase a private car", it is clearly noticed that respondents are more cautious in agreeing with the latter statement, demonstrating their differentiated perceptions towards using a car and owning a car. In other words, having a car is not only meant to meet transport demand, but is also likely to carry additional values which car-sharing might be less capable to provide.

Before we move to the modeling analysis, the following hypotheses are proposed to show in what ways we expect the latent variables could influence shared mobility choices:

- Commuters who are more willing to be a low-carbon traveler would be more likely to use bike-sharing and car-sharing;
- Commuters who are more satisfied with cycling environment would be more likely to use bike-sharing;
- Commuters who are car-sharing advocates would be more likely to use car-sharing.

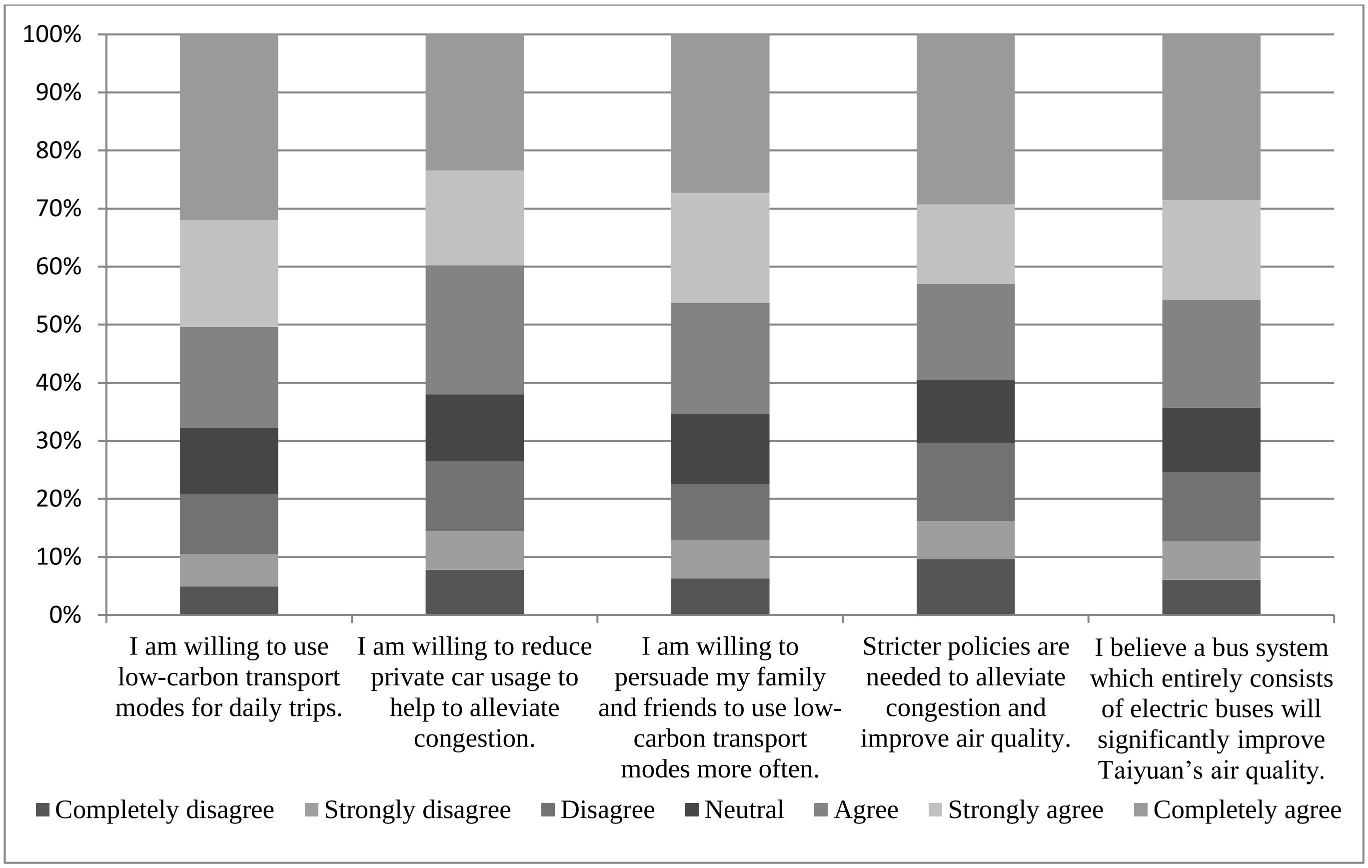

Fig. 1. The Indicators of "Willingness to be a green traveler" (N = 3,486)

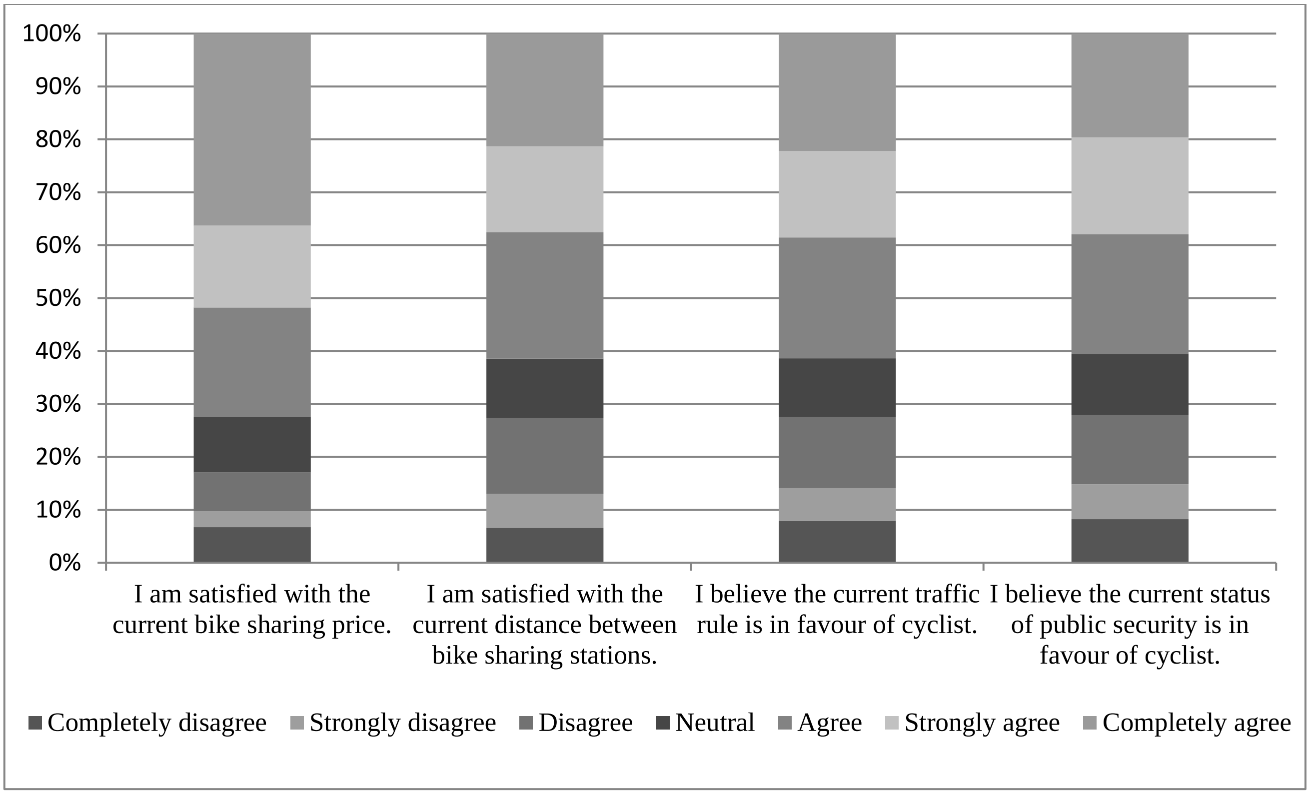

Fig. 2. The Indicators of “Satisfaction with cycling environment” (N = 3,486)

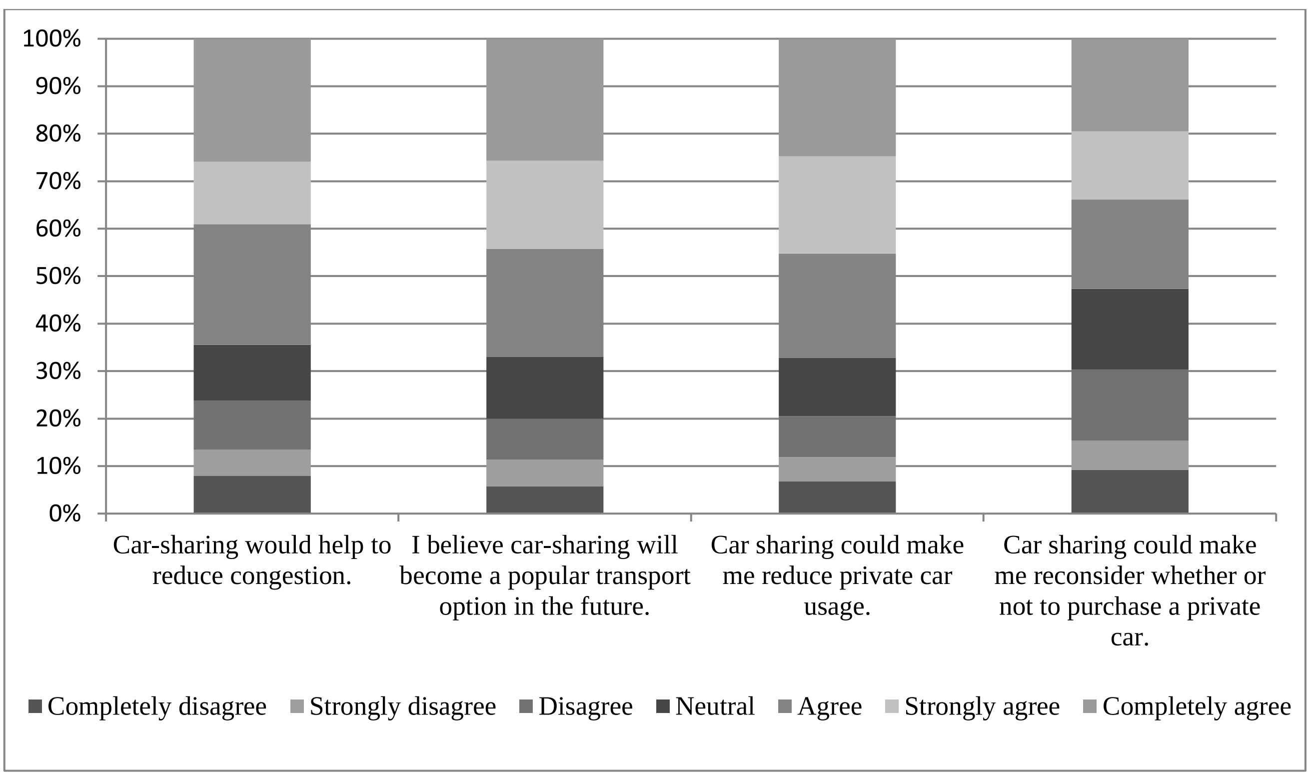

Fig. 3. The Indicators of “Advocacy of car-sharing service” (N = 3,486)

3. MODEL DEVELOPMENT

Before the latent construct is introduced, a base model with nested logit (NL) structure is developed to evaluate the effects of different explanatory variables (attributes presented in the SP survey and socio-economic factors) on mode choices while taking into account inter-alternative correlation given the fact that alternatives were labeled in the SP survey and could possibly share unobserved attributes. The model is specified after many rounds of tests to drop out the variables with highly insignificant effects and to identify the appropriate forms of including variables in utility functions. Several variables that are measured in categorical forms by the survey, such as air pollution, age and household income, are transferred to continuous forms by taking the average value of each category/level. However, only the air pollution effect measured in this way turns out statistically significant in our tests; whereas for age and household income, eventually their categories are grouped in dichotomy (i.e. the lower half and the upper half), as suggested by the test results, to more clearly display their effects. Moreover, systematic taste heterogeneity is studied by evaluating the interaction effects between socio-economic factors and SP attributes. Such a way of analysis has been increasingly adopted in discrete choice literature as it would help reveal whether an attribute could be differently perceived by different social groups of choice makers (Cherchi and Ortúzar, 2011; Ortúzar and Willumsen, 2011). Table 3 provides a summary of the explanatory variables in the model and their measured values.

TABLE 3 Explanatory Variables and Measurements

Variable	Measurement
Air pollution	air quality index (AQI) by taking the average value of each level (25 for excellent level ‘0-50’, 75 for good level ‘51-100’, 125 for light pollution ‘101-150’, 175 for medium pollution ‘151-200’, 250 for heavy pollution ‘201-300’, 400 for terrible pollution ‘above 300’)
Rain	1 if weather is rainy, 0 if otherwise
Temperature	temperature in °C
Travel cost	in RMB
Travel time	in min
Access time	in min, walking time to stations/parking spots

Wait time	in min, waiting time at bus stop
App availability	1 if a smart phone application is available, 0 otherwise
Gender (female)	1 if gender is female, 0 if male
Age (under 35)	1 if age is in the lower half categories in the survey (i.e. "under 18" or "18-25" or "26-35"), 0 if in upper half (i.e. "36-45" or "46-59" or "60 or above")
Household income (below ￥9,000)	1 if household monthly income is in the lower half categories in the survey (i.e. "under ￥3000" or "￥3000-￥6000" or "￥6000-￥9000"), 0 if in upper half (i.e. "￥9000-￥15000" or "￥15000-￥30000" or "over ￥30000")
Educational level (not have a degree)	1 if educational level is in the lower half categories in the survey (i.e. "high school or below" or "college"), 0 if in upper half (i.e. "undergraduate" or "graduate and above")

Next, to incorporate the latent variables, we develop an ICLV model which consists of a latent variable model and a discrete choice model (Ben-Akiva et al., 2002; Walker and Ben-Akiva, 2002; Bolduc et al., 2005; Bolduc and Alvarez-Daziano, 2010). The former part evaluates the latent variables using a set of structural equations (Eq. 1) and a set of measurement equations (Eq. 2). The structural equations aim to identify the causes of the different attitudes and perceptions among individuals. The measurement equations intend to establish a relationship between the indicators from survey results and attitudes and perceptions; in other words, create a channel to observe/measure the latent variables. It is also noteworthy that the indicators are imported into our model under their original ordered format (i.e. 7-point Likert-scale) rather than via a continuous approximation. For the discrete choice model, we use the nested logit model that has been developed earlier and meanwhile introducing the latent variables via two specifications; one model studying their linear effects in the utility functions (Eq. 3) and one model studying their interaction effects with travel time/cost (Eq. 4). As a result, we can find out how the VTTS estimation could be affected by the different forms of model specification (additionally, a model that tried to combine Eq. 3 and 4, i.e. capturing both effects at the same time, was also tested but failed to converge in the model computation phase). The latent variable model and the discrete choice model are simultaneously estimated using a maximum likelihood estimator (Raveau et al., 2010). The estimation is conducted in Pythonbiogeme (Bierlaire, 2016a). In order to accommodate 3 latent variables in a single ICLV model, Monte-Carlo integration is used to handle the multi-dimensional integrals (McFadden, 1989;

Bierlaire, 2016b). Random numbers are generated using MLHS method (Hess et al., 2006) with 1,000 uniform draws employed to achieve a good balance between output precision and model estimation time (Bierlaire, 2015). The complete modeling framework is described by Fig. 4.

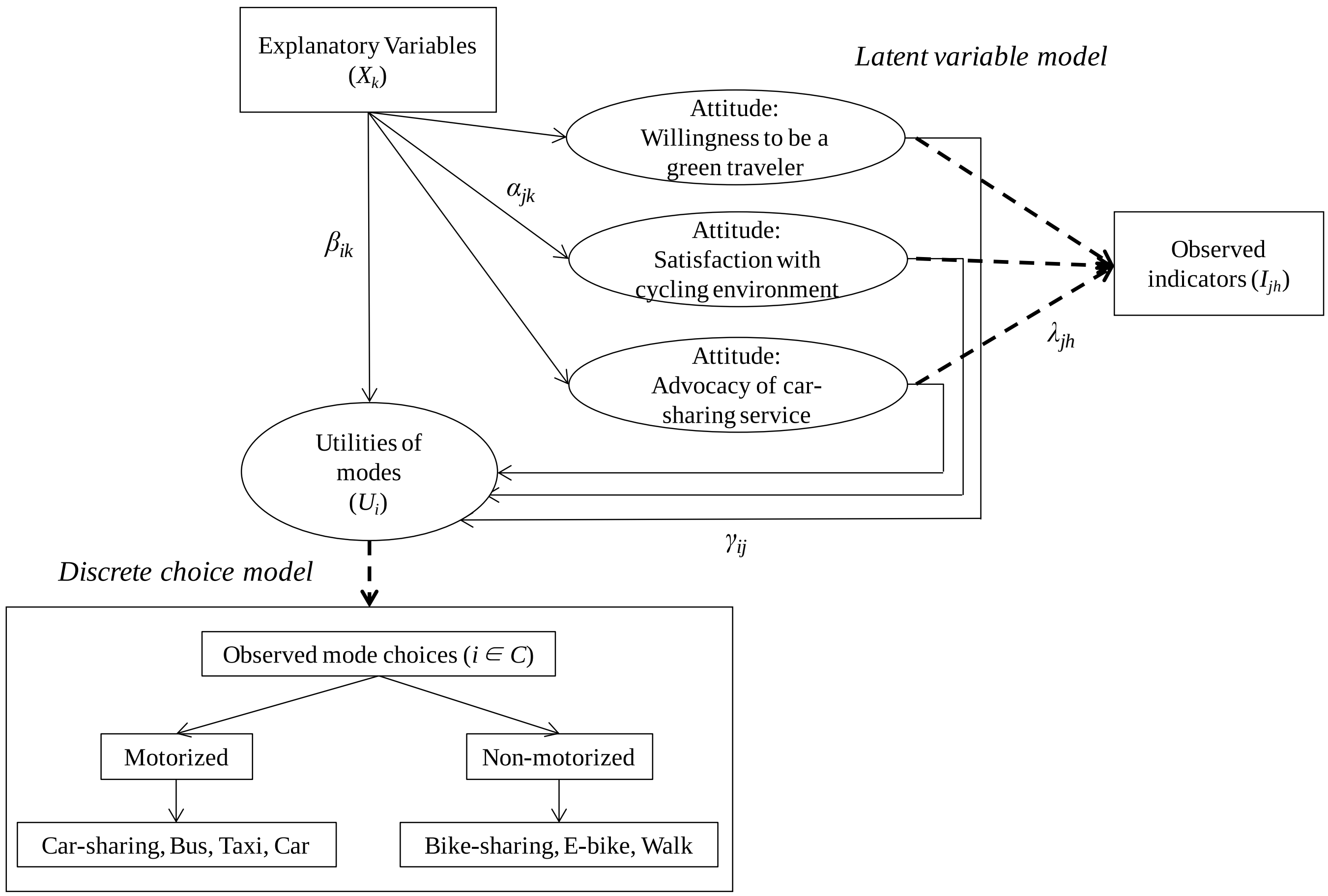

Fig. 4. An ICLV model with 3 latent variables and a nested logit discrete choice model

The mathematical presentation of the modeling framework is given as follows:

Structural equation (latent variable model):

$$ATT_j = \mathrm{A}_j + \sum_{k=1}^{K} \alpha_{jk} X_k + \sigma_j \omega_j \tag{1}$$

Measurement equation (latent variable model):

$$I_{jh} = \Lambda_{jh} + \lambda_{jh} ATT_j + \sigma_{jh} \upsilon_{jh} \tag{2}$$

where ATT_j is the vector of latent factors, X_k is the vector of explanatory variables and α_{jk} is the vector of estimated coefficients (A_j is the vector of intercepts). I_{jh} is the vector of indicators through which the latent factors are manifested and their effects on the indicators are revealed by the parameter vector λ_{jh} (Λ_{jh} is the vector of intercepts). ω_j and υ_{jh} are the disturbance and measurement errors normally distributed across individuals with mean 0 and variance 1, $\sim N(0,1)$, and σ_j and σ_{jh} are their effects (standard deviation) respectively.

Utility function (discrete choice model):

$$U_i = \mathrm{B}_i + \sum_{k=1}^{K} \beta_{ik} X_k + \sum_{j=1}^{J} \gamma_{ij} ATT_j + \varepsilon_i \tag{3}$$

$$U_i = \mathrm{B}_i + \sum_{k=1}^{K} \beta_{ik} X_k + \sum_{j=1}^{J} \sum_{k=1}^{K} \gamma_{ij} ATT_j X_k + \varepsilon_i \tag{4}$$

where U_i is the utility associated with an alternative mode, X_k is the vector of explanatory variables and any form of interactions among them (e.g. systematic taste heterogeneity), and β_{ik} is the vector of estimated coefficients (B_i is the vector of alternative specific constants). The effects of latent factors are revealed by the parameter vector γ_{ij} . ε_i is the disturbance and measurement error i.i.d. extreme value distributed.

As the utility functions are estimated under a nested logit structure, the choice probability functions will become:

Choice of a nest (upper level):

$$P_{M_s} = \frac{e^{\lambda_s IV_s}}{\sum_{z=1}^{Z} e^{\lambda_z IV_z}} \tag{5}$$

Choice of an alternative inside a nest (lower level):

$$P_{i|M_s} = \frac{e^{V_i/\lambda_s}}{\sum_{j \in M_s} e^{V_j/\lambda_s}} \qquad (6)$$

General choice of an alternative:

$$P_i = P_{M_s} P_{i|M_s} \qquad (7)$$

where P is choice probability, M_s represents the nest s ($s = 1, \ldots, z$), IV is the expected maximum utility for the choice of alternatives inside a nest, λ is the scale parameter measuring the different variances across nests.

Finally, there is an important issue to be considered regarding intra-person correlation (panel effect). Although the data cleaning procedure (i.e. we only kept commute trips) has reduced the number of mode choices in the sample, there are still many respondents having more than one mode choice observation. Hence, when we analyzed the base model in the beginning (i.e. an NL model without latent variables), two mixed-nested logit (mixed NL) models were also tested, one with panel effect captured linearly as error components in utility functions and the other with random taste coefficients applied to alternatives' travel times and costs. The mixed NL structure can simultaneously evaluate inter-alternative and intra-person correlations while disentangling the two effects clearly (Hess et al., 2004; Ortúzar and Willumsen, 2011). In both mixed NL models, significant panel effect was detected, although the significance lost immediately when later on adding the two corresponding types of latent construct in the ICLV models (Eq. 3 and Eq. 4). Such a difference implies the three latent variables could help explain a great part of taste heterogeneity across respondents, while the remaining part of heterogeneity that is still unknown/unexplained seems to be trivial (Vij and Walker, 2016). Thus, for the discrete choice sub-model in the ICLV analysis, we finally adopted the NL structure as explained in the beginning to present only the inter-alternative correlation. A significant amount of computation time was also saved by getting rid of the insignificant panel effect estimated with the additional mixed logit kernel (especially when in our case the sub-parts of an ICLV model are simultaneously estimated; Raveau et al., 2010). In fact, the strategy here is very much in line with existing practices where MNL form is frequently presented as the base model in ICLV studies with panel-structured data (e.g. e.g. Abou-Zeid et al., 2010; Raveau et al., 2010; Kamargianni and Polydoropoulou, 2013; Kamargianni et al., 2015; and there are more), since the latent construct could often replace and decompose the unknown heterogeneity into different parts that correspond to specific attitudes and perceptions; in other words, even more insights can be obtained by opening the 'black box' (Vij and Walker, 2016). Nevertheless, in the next section, we will also present the results from a mixed NL model (the one with random coefficients) to make a comparison with its corresponding ICLV form (Eq. 4), in terms of their model performance and the VTTS estimates followed.

4. RESULTS AND DISCUSSIONS

4.1 Latent Variable Model

To start with, Table 4 presents the results of the latent variable model. For the structural equations, we assessed the effects of a variety of socio-economic factors on personal attitudes and perceptions, including gender, age, household income, educational level, marital status and job types. The first four are detected with their significant associations with at least one latent variable while the last two do not demonstrate any significant effects (and thus dropped out). It is found that gender and age could significantly affect all three latent variables. Specifically, female commuters are more willing to travel with green modes and tend to be more favorable towards car-sharing, but meanwhile, they are less likely to be satisfied with the cycling environment in the city. For age effect, the younger generation (under 35) are found to hold relatively negative attitudes across all three cases. The other two factors, household income and educational level, the former seems have no effect on the willingness to be a green traveler while the latter has no effect on the satisfaction with cycling environment. Nevertheless, it is also revealed that those who are less wealthy could be more likely to be satisfied with cycling environment and those who are less educated could be less willing to be a green traveler; in addition, both groups are found to be less favorable towards car-sharing. Generally speaking, most of the discovered impacts can be interpreted intuitively, e.g. it is as expected that female travelers are more sensitive to the surrounding issues when they cycle and thus more difficult to be satisfied, wealthier people are more likely to use car and therefore tend to advocate a car-sharing service, and those who are more educated are usually more aware about environment-related issues and hence more willing to adopt a green travel style, etc. In contrast, the interpretation of age effect should be treated with more cautions. The group of those who are above the age of 35 is found to be more willing to be a green traveler. Although this may contradict to the expectation that younger generation could be more conscious to environmental challenges and willing to take actions, the result is in fact in line with some earlier findings from various case studies (Johansson et al., 2006; Bolduc et al., 2008; Jensen et al., 2013; Bahamonde-Birke and Hanappi, 2016). These works are from developed countries where the general public tends to be more concerned about environment-related issues, and the gap in educational background across age groups are relatively small. Hence, their young people may not be the only generation that is willing to take actions to tackle environmental challenges. However, in our research that is from a developing country which has a different phase of development to the case study areas above, we may need other explanations behind with more robust evidence from the future, to compare to the detected phenomenon in this work. Moreover, we observe a negative relationship (with a large t-statistic) between the younger generation and advocacy of car-sharing service, which is also an interesting result since car-sharing users tend to be young as per the findings in some earlier studies (Jorge and Correia, 2013). Again, further research would be needed to explore any intrinsic factors that might result in such an outcome.

With regard to the measurement equations, the results show that all the indicators are positively associated with the three latent variables, which are in line with our expectations. In other words, the more the respondents hold positive attitudes (i.e. willing to be a green traveler, satisfied with cycling environment and advocate car-sharing service), the more they will agree with the selected statements in the survey. For each latent variable, the parameters of one of the indicators are normalized to the base values as per the model specification requirement (Bierlaire, 2016b).

TABLE 4 Results: Latent Variable Model

	Structural equation	
	coefficient	**t-statistic**
Willingness to be a green traveler		
A_{green}	1.32	23.15
Gender (female)	0.74	13.90
Age (under 35)	- 0.13	- 2.45
Educational level (not have a degree)	- 0.22	- 4.19
σ_{green}	2.07	56.22
Satisfaction with cycling environment		
A_{cycle}	- 0.47	- 5.88
Gender (female)	- 0.34	- 6.57
Age (under 35)	- 0.25	- 4.82
Household income (below ￥9,000)	1.78	22.05
σ_{cycle}	2.07	49.70
Advocacy of car-sharing service		
$A_{carshare}$	2.08	23.73
Gender (female)	0.67	12.72
Age (under 35)	- 0.89	- 15.54
Household income (below ￥9,000)	- 0.38	- 5.15
Educational level (not have a degree)	- 0.84	- 14.68
$\sigma_{carshare}$	2.18	54.77
	Measurement equation	
	coefficient	**t-statistic**
Willingness to be a green traveler		
Λ_{green1}	0.24	9.45
Λ_{green2}	- 0.25	- 9.31
Λ_{green3}	0	-
Λ_{green4}	0.11	2.79
Λ_{green5}	0.40	12.16
λ_{green1} (I am willing to use low-carbon transport modes for daily trips.)	0.99	69.99

λ_{green2} (I am willing to reduce private car usage to help to alleviate congestion.)	0.95	66.40
λ_{green3} (I am willing to persuade my family and friends to use low-carbon transport modes more often.)	1	-
λ_{green4} (Stricter policies are needed to alleviate congestion and improve air quality.)	0.82	43.12
λ_{green5} (I believe a bus system which entirely consists of electric buses will significantly improve Taiyuan's air quality.)	0.71	44.83
σ_{green1}	0.96	43.81
σ_{green2}	1.16	53.84
σ_{green3}	1	-
σ_{green4}	2.09	57.40
σ_{green5}	1.75	57.90
Satisfaction with cycling environment		
Λ_{cycle1}	1.12	29.64
Λ_{cycle2}	0.32	11.29
Λ_{cycle3}	0.12	4.69
Λ_{cycle4}	0	-
λ_{cycle1} (I am satisfied with the current bike sharing price.)	0.79	37.62
λ_{cycle2} (I am satisfied with the current distance between bike sharing stations.)	0.64	39.35
λ_{cycle3} (I believe the current traffic rule is in favor of cyclist.)	0.95	57.42
λ_{cycle4} (I believe the current status of public security is in favor of cyclist.)	1	-
σ_{cycle1}	2.15	52.94
σ_{cycle2}	1.80	57.61
σ_{cycle3}	1.35	49.69
σ_{cycle4}	1	-
Advocacy of car-sharing service		
$\Lambda_{carshare1}$	- 0.21	- 8.11
$\Lambda_{carshare2}$	0.01	0.20*
$\Lambda_{carshare3}$	0	-
$\Lambda_{carshare4}$	- 0.33	- 10.91
$\lambda_{carshare1}$ (Car-sharing would help to reduce congestion.)	1.01	66.24
$\lambda_{carshare2}$ (I believe car-sharing will become a popular transport option in the future.)	1.01	75.61
$\lambda_{carshare3}$ (Car sharing could make me reduce private car usage.)	1	-
$\lambda_{carshare4}$ (Car sharing could make me reconsider whether or not to purchase a private car.)	0.77	50.71
$\sigma_{carshare1}$	1.16	52.15
$\sigma_{carshare2}$	0.77	38.55
$\sigma_{carshare3}$	1	-

$\sigma_{carshare4}$	1.68	62.36
* parameter values not meeting the 95% significance level		

4.2 Discrete Choice Model

The results from four different mode choice models are compared in Table 5. The first column gives the nested logit mode choice model without adding the latent variables. Inter-alternative correlation appears to be significant since the sampled commuters are found to consider between motorized and non-motorized options first before making a specific mode choice. Besides, the nesting parameter μ (where $\mu = 1/\lambda$, and λ was defined earlier in Eq. 5 and Eq. 6) is greater than 1, which complies with the model specification requirement (Hess et al., 2004).

The shared mobility choices, bike-sharing and car-sharing, could be influenced by a variety of factors. Among different natural environmental conditions, air pollution is found to affect the two choices in an opposite way, and that is an increase in air pollution level would decrease the utility of using bike-sharing while making car-sharing a more appealing option. By observing also the negative impact on walk choice and positive impacts on taxi and car choices, it is possible to argue that air pollution would make travelers prefer modes that have a closed space (car-sharing etc.) rather than those with more exposure (bike-sharing etc.). The other two natural environmental conditions, rainy weather and temperature, are not found with significant impacts on commuters' shared mobility choices. For trip and mode attributes, as we have expected, travel time and cost are both negatively correlated with bike-sharing and car-sharing usage. In addition, an available smart phone application would increase the probability to choose car-sharing while no significant impact is detected for its correlation with bike-sharing choice. The difference is possibly due to the different levels of familiarity (and thus different degrees of app dependence) with the two services, especially given that bike-sharing has been extensively used in the city for many years whereas to date car-sharing is still not a widely available travel option. Systematic taste heterogeneity is also captured by detecting the significant interaction effects between a number of aforementioned attributes and socio-economic variables. For instance, details are obtained with respect to the age effect on bike-sharing choice, i.e. both air pollution and travel cost are negatively correlated with bike-sharing usage; however, an age group would possibly value these effects differently and in our case that is the younger commuters (under 35) would be more anxious towards the negative impact of air pollution while worrying less about travel cost. It should also be noted that the younger commuter group actually share a positive travel cost coefficient in average (magnitude of the positive interaction effect 0.354 is greater than the negative main effect 0.332), which means their behavior is not economically rational (Hess et al., 2005). The implication is bike-sharing travel cost might have been a less important concern for the younger commuters making mode choice in our survey (i.e. overwhelmed by other factors/attributes when trade-offs are needed), although it is difficult to further conclude whether it could be due to these travelers are generally more advantaged in economic status as personal income measure is not collected in the survey. Nevertheless, we do not expect this to have a severe impact to our study as the net effect is only slightly positive while the main effect remains firmly negative. As for car-sharing choice, the only interaction effect that turns out significant is between educational level and travel cost where less educated commuters have weaker preference than more educated commuters, while an increase in travel cost would further push those less educated away from choosing car-sharing.

Given our focus on the two shared mobility services, factors affecting other mode choices will not be discussed in details. Overall, most of the factors have the expected impact signs apart from two interaction effects, one between car travel cost and educational level, and the other between bus travel cost and household income. For the former one, the issue is similar to the aforementioned positive bike-sharing travel cost coefficient among younger commuters, i.e. now it is the positive car travel cost coefficient among those better educated (that is those having a degree; note: the presented negative interaction effect is for those not having a degree, which means interacting with those having a degree would make the sign positive with the same magnitude); however, there may exist one more explanation for the car travel case, which is commonly known as 'prestige effect' (Hess et al., 2005), especially when we also see the weak main effect of car travel cost (although it is still negative). For the latter one, the positively interacted effect implies poorer people are less worried about bus travel cost, and this may however be caused by the characteristics of our dataset where most bus travellers come from the less wealthy households with very cheap fares paid for using the service. As such, many of them are found to stick with bus as their travel choice, even when there is a price increase in our SP scenarios; this may result in a positive coefficient for the interaction effect. Another issue that is worth mentioning is we adopt alternative-specific coefficients for travel time and travel cost variables, and the detected values significantly differ across the alternatives. The findings imply the marginal disutility of time and cost varies by modes, possibly a result of the different tastes on different travel options (Wardman, 1998; Mackie et al., 2003; Shires and De Jong, 2009). By looking into more details, we can see the marginal disutility of travel time with the use of car-sharing, taxi and car is smaller than the rest of the modes; similarly for travel cost, the marginal disutility on bike-sharing and bus is much larger than which on car-sharing, taxi and car. In common understandings, car-sharing, taxi and car could potentially offer better travel experiences if comparing with some other travel options (e.g. bike-sharing, bus, e-bike and walking), which may help explain their smaller coefficients (the absolute value) of travel time and cost.

The second and the third columns present the model estimation results when the latent variables are involved. As expected, goodness of fit improves by having additional explanatory powers in the models. For the linear effects of latent variables, it is found that a more positive attitude towards "Willingness to be a green traveler" could significantly increase the probability to choose bike-sharing and walk to commute, and make car less likely to be chosen. Nevertheless, car-sharing choice is not found to be significantly affected by such an attitude. One possible explanation is that the city of Taiyuan did not have any operated car-sharing schemes when the survey took place in 2015 and people were probably not aware if the service vehicles would be powered by clean energy or traditional fossil fuel; thus, it is likely that car-sharing was not perceived as a low-carbon travel option among many survey respondents. The other two latent variables, "Satisfaction with cycling environment" and "Advocacy of car-sharing service", do have the results that are in line with our hypotheses, i.e. people that are more satisfied with cycling environment would be more likely to choose bike-sharing and those who are car-sharing advocates would prefer to use car-sharing for commute. It is also noteworthy that car-sharing advocates may be less likely to use car given the observed negative impact sign, though the result is not as significant as those discussed above (we decided to present this parameter since the t-statistic demonstrated high significance when testing alone the effect of "Advocacy of car-sharing service", and the 95% significance no longer held when adding all three latent variables in the model). With regard to the interaction effects of latent variables, the impact signs are similar to which in the linear effect model but the taste heterogeneity towards travel time and travel cost is now captured. Most of the interaction effects that are discovered with significance are between the latent variables and travel time, except for car, which instead has travel cost associated with more significant taste heterogeneity by commuters with differentiated attitudes. As for bike-sharing and car-sharing, those with more positive attitudes towards "Willingness to be a green traveler" and "Satisfaction with cycling environment" are found less uncomfortable with longer bike-sharing travel time, and similarly, car-sharing advocates could more easily accept longer car-sharing travel time.

The last column gives the additional results from the random coefficient mixed NL model. By comparing it with the interaction effect ICLV analysis, we can notice the two models almost perform equally well in terms of the fitness indicators given at the bottom of the table. This reflects our hypothesis in section 3 that taste heterogeneity across respondents can be largely explained by the disclosed latent factors, although there may still be an unknown bit out there (as we can see the final likelihood is slightly better in the mixed NL model). Besides, the utility functions (i.e. the alternatives) in which significant taste heterogeneity is found with regard to travel time and cost are consistent between the two models. As we did in the interaction effect ICLV model, randomness in the mixed NL model is tested on travel times and costs for all alternatives; eventually, significant taste heterogeneity is detected on the travel time of bike-sharing, car-sharing and walk, as well as the travel cost of car, which correspond to our findings in the previous column. For the use of bus, taxi and electric bike, no significant taste variations are found at individual level in this case study. More comparisons across models are followed in the value of time analysis.

TABLE 5 Results: Discrete Choice Model

	NL base model		ICLV model – linear effect		ICLV model – interaction effect		mixed NL model– random coef.	
	Coef.	**t-stat**	**Coef.**	**t-stat**	**Coef.**	**t-stat**	**Coef.**	**t-stat**
Bike-sharing								
$\alpha_{bikeshare}$	1.060	7.48	0.641	4.44	1.200	7.95	1.710	7.25
Air pollution	- 0.003	- 4.34	- 0.003	- 4.75	- 0.003	- 4.76	- 0.004	- 4.38
Air pollution * Age (under 35)	- 0.004	- 4.93	- 0.004	- 4.68	- 0.004	- 4.72	- 0.005	- 5.11
Travel cost	- 0.332	- 3.24	- 0.297	- 2.87	- 0.269	- 2.59	- 0.272	- 3.34
Travel cost * Age (under 35)	0.354	3.18	0.359	3.18	0.354	3.13	0.386	2.89
Travel time	- 0.041	- 13.48	- 0.042	- 13.72	- 0.054	- 14.14	- 0.055	- 14.86
Car-sharing								
$\alpha_{carshare}$	- 0.865	- 5.09	- 1.040	- 5.34	- 0.951	- 5.29	- 0.350	- 5.10
Air pollution	0.003	5.81	0.003	5.85	0.003	6.03	0.002	5.88
Travel cost	- 0.016	- 2.70	- 0.015	- 2.62	- 0.017	- 2.68	- 0.017	- 2.29
Travel cost * Educational level (not have a degree)	- 0.010	- 3.28	- 0.009	- 2.92	- 0.009	- 2.93	- 0.006	- 2.58
Travel time	- 0.007	- 3.27	- 0.008	- 3.40	- 0.009	- 3.52	- 0.010	- 2.65
App availability	0.170	2.56	0.181	2.65	0.194	2.68	0.169	3.00
Bus								
α_{bus}	1.270	7.20	1.210	7.10	1.350	7.50	1.330	5.01
Rain	0.283	3.39	0.299	3.40	0.322	3.49	0.274	3.40

Temperature	- 0.012	- 3.83	- 0.012	- 3.82	- 0.012	- 3.75	- 0.012	- 3.65
Temperature * Age (under 35)	- 0.014	- 3.41	- 0.014	- 3.47	- 0.016	- 3.56	- 0.012	- 3.31
Travel cost	- 0.373	- 5.05	- 0.386	- 5.02	- 0.402	- 5.13	- 0.399	- 4.18
Travel cost * Household income (below ￥9,000)	0.128	2.65	0.138	2.75	0.146	2.77	0.110	2.32
Travel time	- 0.015	- 3.82	- 0.016	- 3.92	- 0.016	- 3.86	- 0.016	- 3.61
Travel time * Gender (female)	0.006	3.60	0.006	3.44	0.006	3.53	0.006	3.62
Travel time * Age (under 35)	0.007	2.73	0.007	2.75	0.007	2.82	0.007	2.65
Access time	- 0.049	- 5.80	- 0.050	- 5.81	- 0.051	- 5.84	- 0.045	- 5.69
Wait time	- 0.014	- 2.84	- 0.014	- 2.75	- 0.014	- 2.59	- 0.017	- 2.93
Taxi								
α_{taxi}	- 1.350	- 5.08	- 1.460	- 5.22	- 1.450	- 5.21	- 1.611	- 5.41
Air pollution	0.003	5.13	0.003	5.13	0.003	5.25	0.002	5.10
Rain	0.530	3.79	0.556	3.83	0.590	3.89	0.559	3.08
Travel cost	- 0.018	- 2.11	- 0.019	- 2.13	- 0.019	- 2.04	- 0.017	- 2.51
Travel time	- 0.007	- 0.56*	- 0.006	- 0.47*	- 0.007	- 0.52*	- 0.005	- 0.57*
Walk								
α_{walk}	1.180	3.83	0.874	2.79	1.250	4.02	1.560	2.64
Air pollution	- 0.002	- 4.07	- 0.002	- 4.03	- 0.002	- 4.01	- 0.002	- 4.13
Air pollution * Age (under 35)	- 0.002	- 3.42	- 0.002	- 3.23	- 0.002	- 3.21	- 0.002	- 2.81
Rain	- 0.464	- 3.29	- 0.461	- 3.24	- 0.439	- 3.07	- 0.410	- 2.91
Travel time	- 0.010	- 0.54*	- 0.009	- 0.47*	- 0.002	- 0.08*	- 0.002	- 0.05*
Electric bike								
α_{ebike}	0.705	5.05	0.627	4.70	0.774	5.29	0.779	3.98
Rain	- 0.609	- 5.03	- 0.586	- 4.79	- 0.572	- 4.60	- 0.626	- 5.21
Travel time	- 0.038	- 5.15	- 0.039	- 5.26	- 0.039	- 5.16	- 0.035	- 4.62
Travel time * Age (under 35)	- 0.010	- 2.86	- 0.010	- 2.88	- 0.010	- 2.84	- 0.011	- 3.07
Travel time * Household income (below ￥9,000)	0.016	2.32	0.016	2.35	0.016	2.33	0.014	2.09
Car								
Air pollution	0.002	5.70	0.002	5.79	0.002	5.85	0.002	5.83
Rain	0.339	3.60	0.354	3.58	0.373	3.63	0.411	2.99
Travel cost	- 0.001	- 0.03*	- 0.001	- 0.08*	- 0.017	- 1.20*	- 0.022	- 1.78*
Travel cost * Educational level (not have a degree)	- 0.018	- 3.05	- 0.022	- 3.36	- 0.024	- 3.41	- 0.021	- 3.17
Travel time	- 0.001	- 0.35*	- 0.001	- 0.38*	- 0.001	- 0.18*	- 0.002	- 0.84*
Latent variables (linear effect & interaction effect)								
Green travel-bikeshare			0.173	7.00				
Green travel-walk			0.139	4.80				
Green travel-car			- 0.060	- 3.71				

Cycle satisfaction-bikeshare			0.052	2.27				
Car-sharing advocacy-carshare			0.038	2.65				
Car-sharing advocacy-car			- 0.021	- 1.62*				
Green travel * Travel time-bikeshare					0.004	5.60		
Green travel * Travel time-walk					0.006	3.32		
Green travel * Travel cost-car					- 0.006	- 3.21		
Cycle satisfaction * Travel time-bikeshare					0.002	2.48		
Car-sharing advocacy * Travel time-carshare					0.001	2.57		
Car-sharing advocacy * Travel cost-car					- 0.002	- 1.44*		
Travel time-bikeshare (sd)							0.039	6.72
Travel time-walk (sd)							0.254	10.42
Travel time-carshare (sd)							0.030	5.08
Travel cost-car (sd)							0.253	4.95
Inter-alternative correlation & Model fitness								
$\mu_{motorized}$	1.72	6.07#	1.68	6.11#	1.58	6.32#	1.53	4.60#
Initial (choice) log-likelihood		- 10161.8		- 10161.8		- 10161.8		- 10161.8
Final (choice) log-likelihood		- 8286.2		- 7958.9		- 7956.6		- 7939.1
Likelihood ratio test		3751.3		4407.5		4412.3		4438.4
$\overline{\rho^2}$		0.18		0.21		0.21		0.21

* parameter values not meeting the 95% significance level

t-test against base value of 1

sd: standard deviation

4.3 Policy Implications

Nowadays there is a general interest to promote the usage of shared mobility services, such as bike-sharing and car-sharing, both of which are often seen as more sustainable transport options. Comparing to conventional mode choice studies, an ICLV analysis could potentially offer more inspirations to policy making. By discovering the link between latent factors and mode choice behavior, relevant advertisements or campaigns may be used to try to influence people's attitudes and perceptions, and in turn, affect their decision making (Vij and Walker, 2016). In this research, the model estimation results on the latent construct could yield policy implications in two folds. First, in the discrete choice model, we have found attitudes and perceptions could directly affect the preferences of shared mobility services (the linear effect model). While car-sharing service is favored by its advocates, there are two different latent factors having a positive correlation with the choice of bike-sharing, with one's effect ("Willingness to be a green traveler") significantly outweighing the other's ("Satisfaction with cycling environment"). As a result, when there is limited resource that can be called for policy use (which is often constrained in reality), it could be more effective to promote bike-sharing usage via advertisements or campaigns that aim to encourage people's green lifestyle (e.g. advertisement of environmental protection), rather than working towards cycle satisfaction (e.g. information campaign on city's cycling environment). Second, we can also know from the ICLV model what population segments should be targeted at to effectively send the message of advertisements or campaigns (Vij and Walker, 2016). This comes from the results of the latent variable model where the correlations between socio-economic groups and latent variables are disclosed. In particular, an environmental protection advertisement could be adapted to target males, the younger generation (under 35) and those less educated (without a degree) to try to change their relatively negative attitudes towards "Willingness to be a green traveler". It can often be achieved by choosing a lead actor that represents the corresponding demographic groups (e.g. young or male), and making the strapline more understandable or better communicate with the targeted population (e.g. less educated). Similarly, for an information campaign on city's cycling environment, the targeted groups should be females, younger generation and richer households; for a campaign or advertisement that promotes the car-sharing concept, the targeted groups should be males, younger generation, less wealthy and less educated people. Overall, policies could possibly be tailored and become more effective when having the findings from an ICLV model (Vij and Walker, 2016).

4.4 Value of Time

Recalling the arguments that taste heterogeneity, as a result of individuals' differentiated attitudes and perceptions, could be taken into account for more realistic VTTS estimation, this research intends to offer more insights on the extent to which latent factors could have an influence on the estimated VTTS values. Table 6 displays the VTTS estimates for the two shared mobility services resulted from our four mode choice models; 1. the NL base model, 2. latent variables entered linearly in the utility functions, 3. latent variables' interaction effects with travel time/cost are captured, and 4. the random coefficient mixed NL model. For the models #3 and #4, VTTS will be different across individuals so that the mean values are presented.

By comparing across the first three columns, it is easily observed that VTTS for both bike-sharing and car-sharing would increase when having personal attitudes and perceptions in the model, especially when the taste heterogeneity on travel time is captured. Although such an increasing trend is in line with several earlier findings that more restrictive models tend to underestimate the value of time (Hensher, 2001a; Hensher, 2001b; Amador et al., 2005), it should be noted that over-estimation by more restrictive models could also be the case sometimes depending on the chosen variables, functional form and the nature of data, as explained by Amador et al. (2005). Moreover, for both bike-sharing and car-sharing, we found VTTS could increase by around 40% from the NL base model to the ICLV model capturing the interaction effects with travel time. The figure is close to the detected amount of increase in several other works (Algers et al., 1998; Hensher, 2001a; Amador et al., 2005) when allowing the taste of travel time to vary randomly (although, as explained before, the figure should not be seen as a norm since the value would depend on the context of study), and is larger than the amount revealed in Abou-Zeid et al. (2010), i.e. around 7%, which might be a result of having sampled individuals with similar attitudes. In the end, the values found from the random coefficient mixed NL model are pretty close to which in the third column (interaction effect model). Again, this implies the heterogeneous tastes across sampled individuals are well captured in the ICLV analysis through the three latent factors, although the mixed NL model still looks more flexible by producing slightly higher VTTS results.

TABLE 6 Mean Value of Travel Time Savings across Models

	NL base model	ICLV model – linear effect	ICLV model – interaction effect	mixed NL model – random coefficient
Bike-sharing	￥7.4 ($1.1)/h	￥8.5 ($1.3)/h	￥10.3 ($1.5)/h	￥ 10.5 ($1.6)/h
Car-sharing	￥26.3 ($3.9)/h	￥31.7 ($4.8)/h	￥37.8 ($5.7)/h	￥38.9 ($5.8)/h

The above findings reflect a need to derive different VTTS for travellers with differentiated attitudes and perceptions since the value could vary substantially when people have distinct tastes towards travel time/cost (see Fig. 5 for the distributed VTTS). Compared to a standard mixed logit model that can also generate differentiated VTTS after incorporating heterogeneous tastes, an ICLV analysis can nevertheless yield more information such that we can further understand what types of people tend to have relatively low/high willingness to pay (i.e. the black box of taste heterogeneity is opened; Vij and Walker, 2016). We will show this via another set of results below by formulating two contrasting groups, one represents people who have more positive attitudes towards traveling with shared mobility while the other represents those with more negative attitudes, and hence comparing the mean VTTS in the two groups. In the ICLV model that captures interaction effects, the taste of bike-sharing travel time could be affected by both "Willingness to be a green traveller" and "Satisfaction with cycling environment". Therefore, we use the results from structural equations to select individuals whose socio-economic characteristics are all positively correlated with the two latent variables to formulate a group representing those having a positive attitude in general, and vice versa a group for those having a negative attitude. For car-sharing travel time taste that could be affected by "Advocacy of car-sharing service", the same procedure applies to formulate the two contrasting groups.

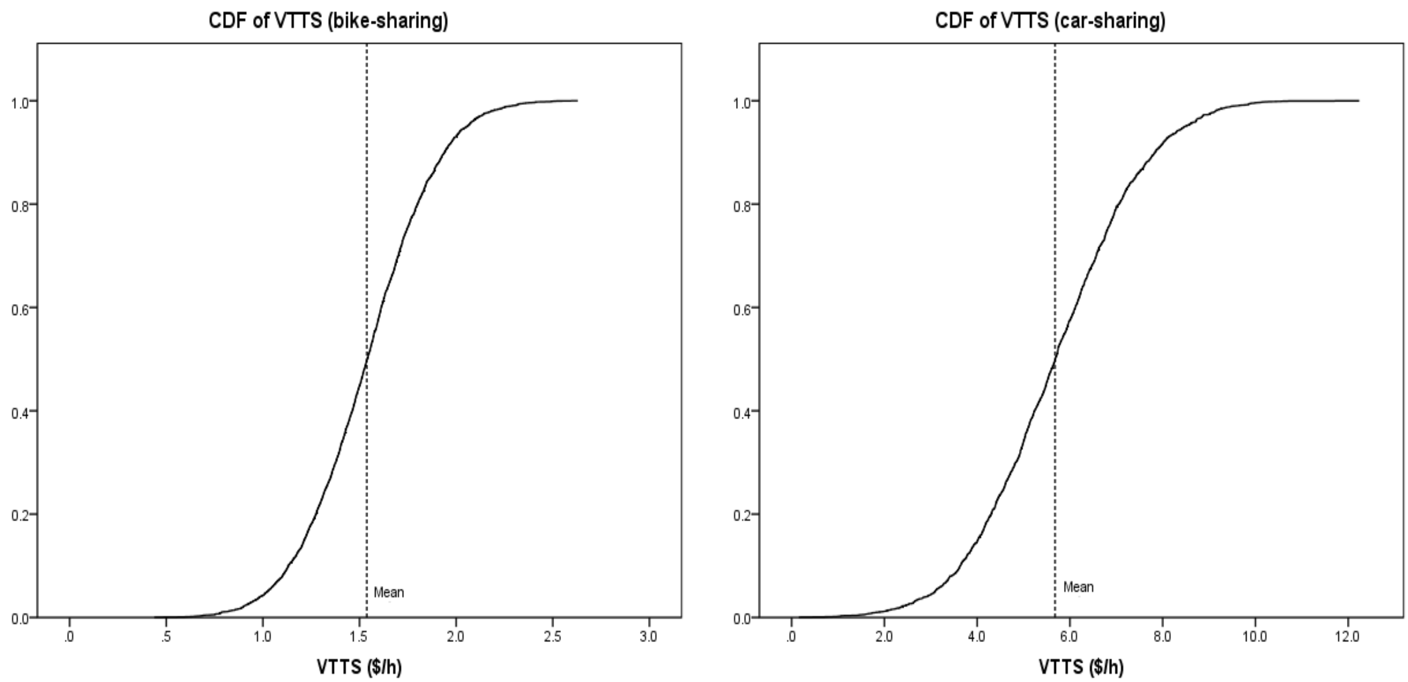

Fig. 5. VTTS distributions among the sampled 3,486 individuals (ICLV model – interaction effect)

Nevertheless, before calculating VTTS for the different groups, it is noteworthy that the interaction effects between travel time and latent factors all have a positive impact sign, as described in section 4.2. Hence, by splitting between positive and negative attitudinal groups, there is a potential for travel time coefficient becoming positive among individuals from the former group, given the fact that more positive attitudes could weaken travel time's negative effect on mode choice behavior. In other words, the marginal opportunity cost of travel time could possibly be offset or even overwhelmed by the marginal benefit of travel time if "travel-experience factors" were involved (Salomon and Mokhtarian, 1998). There could be comfort/pleasure traveling by bike-sharing for those who are more willing to be a green traveller and more satisfied with cycling environment; similarly for car-sharing travel among those who are more supportive to the car-sharing concept. This may affect the VTTS calculation which should be avoided when having a positive travel time coefficient (Hess et al., 2005). Therefore, the impact of travel time is further tested in the positive attitudinal groups for bike-sharing and car-sharing, and negativity is verified before deriving the groups' VTTS values.

Table 7 shows the calculation results. It is revealed that the mean VTTS among those holding a relatively negative attitude could be 20% and 40% higher respectively for bike-sharing and car-sharing than those holding a relatively positive attitude, which, in terms of intuition means that those who are more comfortable with the travel time spent on the two shared mobility services, in general, could have a much lower willingness to pay for travel time savings. This again shows the importance to have different VTTS measures for people with differentiated attitudes and perceptions.

TABLE 7 Mean Value of Travel Time Savings by Groups (ICLV model – interaction effect)

	Being positive towards "green travel" + "cycle satisfaction"	**Being negative towards "green travel" + "cycle satisfaction"**
Bike-sharing	￥9.6 ($1.4)/h	￥11.3 ($1.7)/h
	Being positive towards "car-sharing advocacy"	**Being negative towards "car-sharing advocacy"**
Car-sharing	￥31.7 ($4.8)/h	￥45.5 ($6.8)/h

Moreover, by knowing from the ICLV analysis about the types of people who would rather pay more or pay less for travel time savings, we may use such information to guide the design of pricing policies in the real world. The differentiated VTTS would imply different trade-off preferences across attitudinal groups. This could be particularly important to transport service operators that are interested in understanding how much individuals would be willing to afford a travel cost increase for each unit of their travel time saved (marginal rate of substitution), and hence making adjustments on prices and levels of service offered. In real practice, it may be difficult for an operator to distinguish between customers having differentiated attitudes and thereby offer services differently (in terms of prices and levels of service). However, transport operators could customize their marketing strategies by having the knowledge of the main attitudinal pattern among travelers in a market. For instance, when the market has more travelers with relatively negative attitudes on bike-sharing and car-sharing use (i.e. who care more about travel time savings), efforts could be made towards levels of service improvement (such as introducing shared electric bikes and better-powered vehicles) in return of charging higher prices for the travel time that can be saved; whereas when travelers are mainly those with positive attitudes (i.e. weaker incentives to save travel time), it is perhaps more profitable to invest resources elsewhere rather than focusing on the promotion of faster mobility, which is a less important concern in this case.

An ICLV model could help to identify the main attitudinal pattern in a market, even if the pattern could possibly change over time along with the changes in socio-economic characteristics (e.g. ageing population). In such a case, the results from structural equations could be used to predict attitudinal trends as per the detected links between socio-economic and latent factors (Vij and Walker, 2016). Nevertheless, the use of a given ICLV model output in making predictions should always be handled with caution. This is due to the attitudinal pattern could also change as a result of policy interventions that aim to manipulate individuals' attitudes and perceptions (see section 4.3), which means the results from structural equations may no longer hold as they are discovered. One solution is to make predictions in light of the relationships found between an attitude and its indicators in the measurement equations. This strategy is not frequently seen in existing research due to the difficulty to obtain a good forecast on the potential evolvement path of indicator values. However, as Vij and Walker (2016) noticed, there is an opportunity to adopt "standardized indicators" (i.e. those have been used by other studies in the past) for attitudinal survey designs and analyses, since the paths of change of these indicators are more likely to be available (especially in studies that traced the effect of policy interventions on people's attitudes which were often measured by the same group of indicators at varying time points), and therefore, can support the use of the measurement equations in predicting attitudinal pattern when policy interventions are involved.

At last, it should be noted that the analysis of value of time in this research aims mainly to offer an indication demonstrating the extent to which latent factors could have an influence on the estimated values. A more accurate derivation of VTTS for practical applications would need to involve studies of many other factors such as trip distance (Wardman, 1998; Axhausen et al., 2008), specific local context (Shires and De Jong, 2009), demographics (Jara-Diaz, 2003; Mackie et al., 2003; Trottenberg and Belenky, 2011; Kamargianni et al., 2014) and other potential individual heterogeneity (Bastin et al., 2010).

5. CONCLUSIONS

This work studies how the usage of shared mobility services could be influenced by latent factors. An ICLV modeling framework is adopted to explore the effects of three attitudinal and perceptual factors on bike-sharing and car-sharing choices while simultaneously investigating the potential causes associated with each of the latent variables. A group of Chinese commuters' SP mode choice data is collected for the analysis. It is found that the probability to choose bike-sharing for a commute trip could be positively affected by "Willingness to be a green traveler" and "Satisfaction with cycling environment" and car-sharing choice is positively correlated with "Advocacy of car-sharing service". Implications to policy making are also discussed, in terms of which latent variables could be more effective in helping promote shared mobility usage and therefore should be focused more upon; as well as what population segments should be targeted at when designing advertisements or campaigns to affect people's attitudes and perceptions. Moreover, by taking into account the interaction effects between the latent factors and travel time of the two shared mobility services, significant difference is discovered on the estimated VTTS comparing to the case of not having the latent factors in the model (the NL base model) or adding the them linearly in utility functions. The finding highlights the importance to derive different VTTS for travelers with differentiated attitudes and perceptions, as the tastes towards travel time spent could vary substantially. In other words, there would be different trade-off preferences across attitudinal groups, according to which transport service operators could customize their strategies on prices and levels of service offered.

Although the work offers the state-of-the-art evidence of the extent to which personal attitudes and perceptions could have influence on value of time estimation, several strategies could be adopted by future research to disclose more benefits of mode choice analyses involving latent variables. According to the definitions in Bahamonde-Birke et al. (2017), the three latent variables that we worked with in this research consist of two attitudes (“Willingness to be a green traveler” and “Advocacy of car-sharing service”) and one perception (“Satisfaction with cycling environment”). A difference is, although both attitudes and perceptions can be explained by socio-economic characteristics, the way for how perceptions are formulated can also depend upon mode-related attributes. As a result, studying perceptual factors in a mode choice analysis could potentially bring more practical values (Chorus and Kroesen, 2014), i.e. by having measures that could alter mode-related attributes and in turn affecting perceptions, mode choice behavior and modal substitution pattern could be shifted towards a socially desirable outcome. Due to data constraints (e.g. no available data at disaggregate level on how the surrounded bike-sharing services and cycling infrastructures may differ across individual respondents), we did not extend our analysis to such a dimension to capture the possible influence of mode-related attributes on the perception of cycle satisfaction, which could however be an opportunity for further studies to consider. Another critical challenge encountered by many ICLV studies (including this work) with a simultaneous model estimation structure and relying on maximum simulated likelihood inference approach is the extremely lengthy computation time, especially when multiple latent variables are involved. Bhat and Dubey (2014) proposed an alternative inference approach, maximum approximate composite marginal likelihood, to shorten model estimation time since the dimensionality of integration in the likelihood function will be independent to the number of latent variables and will require no more than bivariate normal cumulative distribution function to be evaluated for likelihood maximization (Bhat, 2011). So far, the application of such a new strategy is only compatible with specific modeling tool (i.e. GAUSS programming language) and would require complex coding inputs. Nonetheless, it is still a good alternative approach, especially when there is a need to handle a broader range of attitudinal and perceptual factors.

ACKNOWLEDGEMENTS

We sincerely appreciate the support from Shanxi Transportation Research Institute in their funding and advice provided during the data collection. We would also like to express our gratitude to the following individuals who made the most significant contributions in the data recording task: Mr Li Peiyu from Shanxi Experimental Secondary School, Mr Hou Juntao from Peking University and Ms Zhao Helan. Finally, we want to thank the three referees for reviewing this paper, from which valuable comments are made to help us improve the work.

REFERENCES

Abou-Zeid, M., & Ben-Akiva, M. (2014). Hybrid choice models. Chapters, 383-412.

Abou-Zeid, M., Ben-Akiva, M., Bierlaire, M., Choudhury, C., & Hess, S. (2010). Attitudes and value of time heterogeneity. Applied Transport Economics-A Management and Policy Perspective. De Boeck Publishing, 523-545.

Algers, S., Bergström, P., Dahlberg, M., & Lindqvist Dillén, J. (1998). Mixed logit estimation of the value of travel time (No. 1998: 15). Working Paper, Department of Economics, Uppsala University.

Alpizar, F., & Carlsson, F. (2003). Policy implications and analysis of the determinants of travel mode choice: an application of choice experiments to metropolitan Costa Rica. Environment and Development Economics, 8(4), 603-619.

Amador, F. J., González, R. M., & Ortúzar, J. de D. (2005). Preference heterogeneity and willingness to pay for travel time savings. Transportation, 32(6), 627-647.

Axhausen, K. W., Hess, S., König, A., Abay, G., Bates, J. J., & Bierlaire, M. (2008). Income and distance elasticities of values of travel time savings: New Swiss results. Transport Policy, 15(3), 173-185.

Bahamonde-Birke, F. J., & Hanappi, T. (2016). The potential of electromobility in Austria: Evidence from hybrid choice models under the presence of unreported information. Transportation Research Part A:

Policy and Practice, 83, 30-41.

Bahamonde-Birke, F. J., Kunert, U., Link, H., & Ortúzar, J. de D. (2017). About attitudes and perceptions: finding the proper way to consider latent variables in discrete choice models. Transportation, 44(3), 475-493.

Bastin, F., Cirillo, C., & Toint, P. L. (2010). Estimating nonparametric random utility models with an application to the value of time in heterogeneous populations. Transportation science, 44(4), 537-549.

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.

Belgiawan, P. F., Schmöcker, J. D., Abou-Zeid, M., Walker, J., & Fujii, S. (2017). Modelling social norms: Case study of students’ car purchase intentions. Travel Behaviour and Society, 7, 12-25.

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.

Bhat, C. R. (2011). The maximum approximate composite marginal likelihood (MACML) estimation of multinomial probit-based unordered response choice models. Transportation Research Part B: Methodological, 45(7), 923-939.

Bhat, C. R., & Dubey, S. K. (2014). A new estimation approach to integrate latent psychological constructs in choice modeling. Transportation Research Part B: Methodological, 67, 68-85.

Bierlaire, M. (2015). Monte-carlo integration with pythonbiogeme, Technical report TRANSP-OR 150806. Transport and Mobility Laboratory, ENAC, EPFL.

Bierlaire, M. (2016a). PythonBiogeme: a short introduction. Report TRANSP-OR 160706, Series on Biogeme. Transport and Mobility Laboratory, School of Architecture, Civil and Environmental Engineering, Ecole Polytechnique Fédérale de Lausanne, Switzerland.

Bierlaire, M. (2016b). Estimating choice models with latent variables with PythonBiogeme, Technical report TRANSP-OR 160628. Transport and Mobility Laboratory, ENAC, EPFL.

Bolduc, D., & Alvarez-Daziano, R. (2010). On Estimation of Hybrid Choice Models, in Stephane Hess , Andrew Daly (ed.) Choice Modelling: The State-of-the-art and The State-of-practice, 259–287.

Bolduc, D., Ben-Akiva, M., Walker, J., & Michaud, A. (2005). Hybrid Choice Models with Logit Kernel: Applicability to Large Scale Models1, in Martin E.H. Lee-Gosselin , Sean T. Doherty (ed.) Integrated Land-Use and Transportation Models, 275 – 302.

Bolduc, D., Boucher, N., & Alvarez-Daziano, R. (2008). Hybrid choice modeling of new technologies for car choice in Canada. Transportation Research Record: Journal of the Transportation Research Board, (2082), 63-71.

Burkholder, M. (2015). The World's 6 Best Bike Share Programs. Available at: http://www.outwardon.com/article/the-worlds-6-best-bike-share-programs/6/

Chen, J., & Li, S. (2017). Mode Choice Model for Public Transport with Categorized Latent Variables. Mathematical Problems in Engineering, 2017.

Cherchi, E., & Ortúzar, J. de D. (2011). On the use of mixed RP/SP models in prediction: Accounting for systematic and random taste heterogeneity. Transportation science, 45(1), 98-108.

Chorus, C. G., & Kroesen, M. (2014). On the (im-) possibility of deriving transport policy implications from hybrid choice models. Transport Policy, 36, 217-222.

Correia, G., Abreu e Silva, J., & Viegas, J. (2010). Using latent attitudinal variables for measuring carpooling propensity. In Proceeding of 12th World Conference on Transport Research. Lisbon.

Daziano, R. A., & Bolduc, D. (2013). Incorporating pro-environmental preferences towards green automobile technologies through a Bayesian hybrid choice model. Transportmetrica A: Transport Science, 9(1), 74-106.

Efthymiou, D., & Antoniou, C. (2016). Modeling the propensity to join carsharing using hybrid choice models and mixed survey data. Transport Policy, 51, 143-149.

Fernández-Heredia, Á., Jara-Díaz, S., & Monzón, A. (2016). Modelling bicycle use intention: the role of perceptions. Transportation, 43(1), 1-23.

Fishman, E., Washington, S., & Haworth, N. (2012). Barriers and facilitators to public bicycle scheme use: A qualitative approach. Transportation research part F: traffic psychology and behaviour, 15(6), 686-698.

Fleischer, A., Tchetchik, A., & Toledo, T. (2012). The impact of fear of flying on travelers' flight choice: choice model with latent variables. Journal of Travel Research, 51(5), 653-663.

Global Opportunity Explorer. (2016). Taiyuan: World's fastest electric taxi fleet overhaul. Available at: http://explorer.sustainia.me/cities/taiyuan-worlds-fastest-electric-taxi-fleet-overhaul

Hao, Y. (2017). Car-sharing market floundering. Available at: http://www.chinadaily.com.cn/bizchina/motoring/2017-03/20/content_28609872.htm

Hensher, D. A. (2001a). The valuation of commuter travel time savings for car drivers: evaluating alternative model specifications. Transportation, 28(2), 101-118.

Hensher, D. A. (2001b). Measurement of the valuation of travel time savings. Journal of Transport Economics and Policy (JTEP), 35(1), 71-98.

Hensher, D. A., Rose, J. M., & Greene, W. H. (2005). Applied choice analysis: a primer. Cambridge University Press.

Hess, S., Bierlaire, M., & Polak, J. (2004). Development and application of a mixed cross-nested logit model. In XXIth European Transport Conference (No. TRANSP-OR-CONF-2006-044).

Hess, S. Bierlaire, M., & Polak, J. (2005). Estimation of value of travel-time savings using mixed logit models. Transportation Research Part A: Policy and Practice, 39(2), 221-236.

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.

Hiles, D. (2015). The World's Surprising Top 8 Bike Share Programs. Available at: http://www.icebike.org/bike-share-programs/

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, T., Song, M., Jiang, Y., Li, M., & Zou, H. (2013). Toward Transit Metropolis: Status Quo Analysis for Chinese Major Cities. Procedia-Social and Behavioral Sciences, 96, 2621-2634.

Johansson, M. V., Heldt, T., & Johansson, P. (2006). The effects of attitudes and personality traits on mode choice. Transportation Research Part A: Policy and Practice, 40(6), 507-525.

Jara-Diaz, S.R. (2003). On the goods-activities technical relations in the time allocation theory. Transportation, 30(3), 245-260.

Johansson, M. V., Heldt, T., & Johansson, P. (2006). The effects of attitudes and personality traits on mode choice. Transportation Research Part A: Policy and Practice, 40(6), 507-525.

Jolliffe, I. (2002). Principal component analysis. John Wiley & Sons, Ltd.

Jorge, D., & Correia, G. (2013). Carsharing systems demand estimation and defined operations: a literature review. EJTIR, 13(3), 201-220.

Kaiser, H. (1958). The Varimax Criterion for Analytic Rotation in Factor Analysis. Psychometrica Vol.23, 187-200.

Kamargianni, M., Ben-Akiva, M., & Polydoropoulou, A. (2014). Integrating social interaction into hybrid choice models. Transportation, Vol.41(6), 1263-1285.

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.

Kamargianni, M., & Polydoropoulou, A. (2013). Hybrid choice model to investigate effects of teenagers' attitudes toward walking and cycling on mode choice behavior. Transportation Research Record: Journal of the Transportation Research Board, (2382), 151-161.

Kim, J., Rasouli, S., & Timmermans, H. (2014). Expanding scope of hybrid choice models allowing for mixture of social influences and latent attitudes: Application to intended purchase of electric cars. Transportation research part A: policy and practice, 69, 71-85.

Kim, J., Rasouli, S., & Timmermans, H. (2017a). Satisfaction and uncertainty in car-sharing decisions: An integration of hybrid choice and random regret-based models. Transportation Research Part A: Policy and Practice, 95, 13-33.

Kim, J., Rasouli, S., & Timmermans, H. (2017b). The effects of activity-travel context and individual attitudes on car-sharing decisions under travel time uncertainty: A hybrid choice modeling approach. Transportation Research Part D: Transport and Environment, 56, 189-202.

La Paix Puello, L. C., & Geurs, K. T. (2015). Modelling observed and unobserved factors in cycling to railway stations: application to transit-oriented-developments in the Netherlands. European journal of transport and infrastructure research, 15(1), 27-50.

Li, W. (2019). A Mode Choice Study on Shared Mobility Services: Policy Opportunities for a Developing Country. Doctoral dissertation, March 2019, University College London.

Li, W., & Kamargianni, M. (2018). Providing quantified evidence to policy makers for promoting bike-sharing in heavily air-polluted cities: A mode choice model and policy simulation for Taiyuan-China. Transportation research part A: policy and practice, 111, 277-291.

Li, W., & Kamargianni, M. (2019). Steering Short-term Demand for Car-sharing: A Mode Choice and Policy Impact Analysis by Trip Distance. Transportation, accepted for publication on 15th May 2019.

Likert, R. (1932). A technique for the measurement of attitudes, Archives of psychology 140: 1–55.

Louviere, J., Hensher, D., & Swait, J. (2003). Stated choice methods: analysis and applications. Cambridge: Cambridge University Press.

Mackie, P.J., Wadman, M., Fowkes, A.S., Whelan, G., Nellthorp, J., & Bates, J. (2003). Values of Travel Time Savings UK. Institute of Transport Studies, University of Leeds, Working Paper 567.

Maldonado-Hinarejos, R., Sivakumar, A., & Polak, J. W. (2014). Exploring the role of individual attitudes and perceptions in predicting the demand for cycling: a hybrid choice modelling approach. Transportation, 41(6), 1287-1304.

McCarthy, O. T., Caulfield, B., & O’Mahony, M. (2016). How transport users perceive personal safety apps. Transportation research part F: traffic psychology and behaviour, 43, 166-182.

McFadden, D. (1989). A method of simulated moments for estimation of discrete response models without numerical integration. Econometrica: Journal of the Econometric Society, 995-1026.

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.

Munoz, B., Monzon, A., & Lopez, E. (2016). Transition to a cyclable city: Latent variables affecting bicycle commuting. Transportation Research Part A: Policy and Practice, 84, 4-17.

Ortúzar, J. de D., & Willumsen, L. G. (2011). Modelling transport. New Jersey: Wiley, 4th Edition.

Paschalidis, E., Basbas, S., Politis, I., & Prodromou, M. (2016). "Put the blame on… others!": The battle of cyclists against pedestrians and car drivers at the urban environment. A cyclists' perception study. Transportation research part F: traffic psychology and behaviour, 41, 243-260.

Paulssen, M., Temme, D., Vij, A., & Walker, J. L. (2014). Values, attitudes and travel behavior: a hierarchical latent variable mixed logit model of travel mode choice. Transportation, 41(4), 873-888.

Piatkowski, D. P., Marshall, W., & Johnson, A. (2017). Identifying behavioral norms among bicyclists in mixed-traffic conditions. Transportation research part F: traffic psychology and behaviour, 46, 137-148.

Raveau, S., Alvarez-Daziano, R., Yanez, M., Bolduc, D., & Ortúzar, J. de D. (2010). Sequential and simultaneous estimation of hybrid discrete choice models: some new findings. Transportation Research Record: Journal of the Transportation Research Board, (2156), 131-139.

Romero, A., Tasciotti, L., & Acosta, F. (2017). Means of transportation choice for the residents of Villavicencio, Colombia: a quantitative analysis. Transportation research part F: traffic psychology and behaviour, 44, 134-144.

Salomon, I., & Mokhtarian, P.L. (1998). What happens when mobility-inclined market segments face accessibility-enhancing policies?. Transportation Research Part D: Transport and Environment, 3(3), 129-140.

Sarkar, P. P., & Mallikarjuna, C. (2018). Effect of perception and attitudinal variables on mode choice behavior: A case study of Indian city, Agartala. Travel Behaviour and Society, 12, 108-114.

Shires, J. D., & De Jong, G. C. (2009). An international meta-analysis of values of travel time savings. Evaluation and program planning, 32(4), 315-325.

Smith, B., Olaru, D., Jabeen, F., & Greaves, S. (2017). Electric vehicles adoption: Environmental enthusiast bias in discrete choice models. Transportation Research Part D: Transport and Environment, 51, 290-303.

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.

Toutiao. (2017). Things about bike-sharing in Taiyuan. Available at: http://www.toutiao.com/i6434389096147206657/

Trottenberg, P., & Belenky, P. (2011). Revised departmental guidance on valuation of travel time in economic analysis. US Department of Transportation, Washington, DC.

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.

Vinayak, P., Dias, F. F., Astroza, S., Bhat, C. R., Pendyala, R. M., & Garikapati, V. M. (2018). Accounting For Multi-dimensional Dependencies Among Decision-makers Within a Generalized Model Framework: An Application to Understanding Shared Mobility Service Usage Levels (No. 18-05777).

Walker, J., & Ben-Akiva, M. (2002). Generalized random utility model. Mathematical Social Sciences, 43(3), 303-343.

Wardman, W. (1998). The value of travel time a review of British evidence. Journal of Transport Economics and Policy, vol. 32, no. 3, 285–316.

Xinhua. (2017). Car-sharing services taking the fast lane in China. Available at: http://www.chinadaily.com.cn/business/motoring/2017-02/15/content_28204616.htm

Yanez, M. F., Raveau, S., & Ortúzar, J. de D. (2010). Inclusion of latent variables in mixed logit models: modelling and forecasting. Transportation Research Part A: Policy and Practice, 44(9), 744-753.