On the Heterogeneity in Consumer Preferences for Electric Vehicles across Generations and Cities in China

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Abstract:

China is currently the world's biggest electric vehicle (EV) market, in which mostly mature consumers in first-tier cities are buying EVs. However, the changing market and policy environment are challenging the sustainability of this trend. This study conducts a nationwide stated preference (SP) experiment in China to examine preference heterogeneity towards EVs across (1) different generations and (2) different tiers of cities. Discrete choice analysis reveals that the tier of cities has a significant effect on adoption preferences for EVs. Surprisingly, consumers in smaller cities exhibit stronger preference for EVs, while an insignificant difference in preference is found between consumers of different generations. The interaction effect between the tier of cities and the generations further demonstrates that younger consumers in small cities most prefer EVs. This can be explained by their evaluations of the psychosocial advantages of EVs and their aspiration for a future of EV-based mobility. This research contributes to the broad literature of technology adoption, but more specifically, the research offers new insights on consumers' EV preference heterogeneity with respect to geographic and demographic dimensions. The study has important business and policy implications relating to the EV transition in China in consideration of the two tested dimensions.

Keywords: Electric vehicles, generation, city, preference heterogeneity, China

1. Introduction

The transition towards electric vehicles (EVs) has global implications for meeting the objectives of sustainable mobility (Tyfield and Zuev, 2018), and this transition is particularly important in China because it is the world's largest car market (Qian and Soopramanien, 2014). Because of the positive impact of EVs in reducing carbon emissions, China has been prioritising and supporting EV production and sales as one of the key strategies in its national sustainable development agenda (Du and Ouyang, 2017). As a result, China became the world's biggest EV market in relation to production and sales at the end of 2016 (Ministry of Industry and Information Technology of China, 2017).

Currently, the development of the EV market in China has two major characteristics. First, the first-tier cities[1] have been leading the current EV market in China, with over 40% market share since 2017 (Sina Auto, 2020). Second, EV buyers in China tend to be older than consumers who purchase conventional petrol cars (Yang et al., 2017). For example, in December 2019, only 15.6% and 19% of battery electric vehicle (BEV) and plug-in hybrid electric vehicle (PHEV) buyers, respectively, were aged 30 years or younger (Daas-Auto Research Center, 2020a), while the proportion of this age group of the entire passenger car market was 27.5% (DaaS-Auto Research Center, 2020b). In addition, the EV market in China is undergoing several policy and market changes, such as phasing out EV purchase subsidies (Zheng et al., 2018). Policies such as providing subsidies designed to boost EV sales have been found to be effective in fostering the adoption of EVs in China, and the recent policy changes have been challenging the sustainability of the current EV market, where the sale growth of EVs in China has been slower since 2018 (China Passenger Car Association, 2020). It is therefore timely and useful to investigate consumer preferences for EVs in China's transition process, and to examine which factors are shaping Chinese consumers' preferences for EVs in this changing market environment.

There are two main research approaches when examining consumer adoption of EVs. The first approach focuses on examining the mechanisms underlying the adoption of EVs or the intention to adopt EVs, including psychological antecedents (e.g. personal values and traits, risk attitude); situational factors (e.g. environment, technology); and contextual factors (e.g. government policies) (Singh et al., 2020). Most of the studies in this stream use survey-based methodology (Kumar and Alok, 2020) and employ structural equation models to test the proposed research hypotheses (e.g. Qian and Yin, 2017). The second approach conducts stated preference (SP) experiments to investigate the effects of product, service and policy attributes on individuals' SPs for EVs (Li et al., 2017), and this stream of research employs discrete choice modelling as the main analytical approach. The present study is in the second stream of literature, and our research contributions differ from those of past research given that we examine new factors that could influence EV adoption (i.e. generational and geographic differences) as well as enhancing the understanding that already exists, as summarised in the following three points.

First, the product attribute perspective of EV adoption posits that the basic utility of using and owning an EV is dependent of functional or tangible factors such as purchase price, running cost, and driving range (Wang et al., 2018). In general, empirical evidence demonstrates that EVs are considered expensive because of their high purchase price (Li et al., 2018), and they are not functionally desirable, mostly because of their limited driving range, which is exacerbated by an insufficient availability of battery charging stations. In the context of China and in particular when we consider its geographic size, driving range is likely to be a more important consideration for Chinese consumers than for consumers who live in geographically smaller countries. It is also important to note that Chinese urban areas are also very large and car owners must also travel long distances within cities.

Second, the limited availability of EV charging services is also recognized as a barrier to the wider adoption and diffusion of EVs (Rezvani et al., 2015). Charging service issues relate to the geographic coverage of public charging stations, workplace charging posts and ability to charge the car at home (Liu, 2012). Home charging is particularly an issue in China because many households live in flats and may be unable to install and have access to their own charging posts at their place of residence (Qian et al., 2019). Besides the coverage, the time required by slow (workplace charging post, home charging post) and fast (public charging station) charging is also an important factor for EV purchase (Junquera et al., 2016).

Third, in relation to policy attributes, extant studies have examined monetary subsidies or tax exemptions, free parking, and access to bus or high-occupancy vehicle lanes (Lieven, 2015) in relation to consumer preferences for EVs. In China, purchase subsidy and vehicle licensing policy are the two major means currently employed by the government to promote the EV market. In contrast, conventional petrol cars are not subsidised and do not enjoy transport-related priority, and they are even regulated with policies that restrict the number of license plates allowed in major cities such as Beijing and Shanghai (Yang et al., 2017). In the Chinese market, such government policies play a critical role in facilitating the mass adoption of EVs because EV adopters are considered either 'subsidy driven' or motivated to purchase EVs because it is the only way to obtain immediate car licensing in some cities (Xing et al., 2016).

However, little empirical attention has been paid to the influences of geographic and generational factors in EV adoption, despite their theoretical significance in transition studies (Hansen and Coenen, 2015). This is an important research gap, particularly because EV adoption is China's focus in its transition towards a new regime of sustainable development. Compared with the conventional literature illustrating system transition in a relatively abstract and generalized form, recent literature has argued that more attention should be paid to the specific and diverse elements that are overlooked in transition processes (Coenen et al., 2012; Hansen and Coenen, 2015), such as geography and demographics. More specifically, Wang et al. (2012) argue that the future growth of the Chinese EV market will increasingly come from second-tier and smaller cities, which have a growth rate that is higher than the national growth rate of EV adoption (DaaS-Auto Research Center, 2018). Furthermore, McKinsey indicates that one major trend in the Chinese consumer market is the emergence of the young generation born in the 1990s (which is often labelled the '90s generation') (Baan et al., 2017). This generation is purported to become the main driver of consumption growth in China between 2017 and 2030, and will be more important for consumption than any other demographic segment in this period (Baan et al., 2017). Thus, demographic diversity has significant implications for the Chinese market in that there is a demographic division of those born before and after the beginning of China's second wave of 'reform and opening up' in the 1990s.

Empirical studies on EV adoption in China tend to focus more on young consumers in big cities without explicitly examining whether and how geography and generation together play an important role in consumption. We consider that insufficient research attention has been paid to investigating geographic and demographic heterogeneity for EV preference in China, particularly because most existing studies surveyed potential EV adopters only in first-tier and second-tier cities (e.g. Helveston et al, 2015). While He and Zhan's (2018) sample includes respondents from smaller cities, they oversampled young people in China (73.5% aged younger than 41). This means that previous research has generally overlooked the preference heterogeneity of potential EV adopters across different geographic and generational groups in China.

By explicitly considering these two key drivers of consumer preferences that have been overlooked in the research on transition towards EV mobility, we formulated the following two interrelated research questions: (1) Do Chinese consumers from different generations and living in different tiers of cities have heterogeneous preferences for EVs? (2) How can their preference heterogeneity be explained? We adopt the terms '90s generation' and 'pre-90s generation' to refer to the younger and older generations, respectively. Individuals in the former group were born in the 1990s and those in latter group were born in the 1980s or earlier. In addition, we consider and define three categories of cities: big cities (which includes first-tier and second-tier cities, both of which have more than 5 million urban population); midsized cities (which includes third-tier cities, which have 1–5 million urban population); small cities (which includes fourth-tier and fifth-tier cities, both of which have less than 1 million urban population).

For our empirical investigation, we collect and use SP data from 24 regions across China. This involves conducting choice-based conjoint experiments among a sample of 989 respondents from two generations in the same household across five tiers of cities. We then conduct discrete choice modelling and choose the nested logit (NL) model that performs best at capturing heterogeneity effects across generations and tiers of cities in relation to consumers' EV preferences. In addition, we introduce a range of subjective evaluation measures related to consumers' perception of the current and future roles of EVs to explain preference heterogeneity across different generations and tiers of cities (Noppers et al., 2015).

This study contributes to the literature in the following five ways. First, we contribute to the literature on technology adoption and transition studies by demonstrating the value of generational and geographic variables in explaining adoption preferences in transitioning from one regime to another. Second, we extend the literature on consumer preferences for EVs in China by collecting nationwide empirical data and examining the effects of two important but overlooked factors: generational effects and geographic effects in China. Third, we combine SP experimentation with subjective measures of consumers' perception of the functional, environmental and psychosocial aspects of EVs, which is novel in explaining the heterogeneous preferences identified in the experiment. Fourth, we highlight the crucial role of future aspirations in shaping consumer preferences for EVs across different generations and in different cities in China. Fifth, the study makes a significant contribution to the existing literature on the future trajectory of EV diffusion in the Chinese market.

The remainder of this paper is organised as follows. Section 2 discusses the generational and geographic factors in relation to consumer preferences for EVs, and describes the research method, including the design of the SP experiment, the evaluation measures for EVs, as well as the data collection procedure. Section 3 presents and discusses the results. Section 4 discusses the major contributions and the implications for policy makers and business practitioners. Section 5 summarises the research contributions, discusses the study limitations and presents directions for future research.

2. Research Hypotheses and Methodology

2.1. Research hypotheses

The existing literature generally suggests that younger people are more open than older people to accepting new ideas and adopting innovative products (Huh and Kim, 2008; Lee, 2008). In addition, members of the current younger generation are also more aware of environmental issues and are thus more likely to be concerned about sustainability and sustainable consumption (Gurtner and Soyez, 2016). In the context of China, these characteristics of the 90s generation mean that this generation can be expected to be more inclined to adopt EVs than the pre-90s generation, with following three principal reasons.

First, compared with users of conventional internal combustion engine vehicles (ICEVs), younger consumers, who have limited driving experience, are likely to find it easier to adapt to the new routines required to drive EVs. That is, driving EVs requires ICEV drivers to learn something new and change their behavioural routines to adapt to the product's technical requirements (Lane and Potter, 2007). However, the consumers from the 90s generation generally have less ICEV driving experience than the older generation, which enables them to adapt to the innovative product features of the EVs more easily than the older consumers, thus making the 90s generation more inclined to purchase an EV (Accenture Research Center, 2018). Second, Chinese consumers from the 90s generation were born in the era in which the country promoted a market economy (i.e. since 1992), and have lived only during the experience of this period of China's unprecedented economic growth and modernisation (Luo and Wang, 2015). As a result, consumers from this young generation are more risk taking in their consumption process, inclined to conspicuous consumption, and more willing to pay a high price premium to buy products with innovative features (Zhou and Wong, 2008). Third, members of the 90s generation generally have a higher level of fashion consciousness (Gong et al., 2004), and are more experienced in using digital technology (Palfrey and Gasser, 2008), which makes them more adaptive to the digital in-vehicle technologies in EVs.

The 90s generation represents the target market segment for EVs. The best-selling EVs are purposefully designed to be fashionable and trendy (Zach, 2017) and to incorporate innovative digital features in the vehicles (e.g. voice control, mobile data communication, and automatic parking assistance) (Moran et al., 2010) to reduce driving complexity for car driving beginners. Therefore, we hypothesise the following generational effect on EV adoption.

H1: Consumers from the 90s generation exhibit stronger preferences for EVs than those from the pre-90s generation.

The existing literature posits that city size is a crucial factor in studying markets, particularly in relation to how consumers in cities differ from other consumers (e.g. Song et al., 2015). Cardoso and Meijers (2016) contrast big cities and smaller cities and find that big cities provide interactive environments that are more enabling for innovation and provide their residents with wider access to goods and services. New technological products are usually introduced into bigger cities in China before being launched into smaller cities (Cui and Liu, 2000). Thus, consumers from big cities have earlier access to technological innovations and develop knowledge and preferences earlier than do those from small cities (Huang and Qian, 2018).

In addition, different tiers of cities in China have different levels of transport infrastructure and economic development. In general, the bigger cities have a higher development level of EV charging infrastructure, which has made EVs more desirable in these cities. In addition, in the early years, the central government of China prioritised the marketisation of EVs through its EV incentive programmes in 25 pilot cities (Ministry of Science and Technology of China, 2013), more than half of which are first- or second-tier cities.[2] Because of their greater exposure to EVs, consumers in those bigger cities may have a higher level of EV knowledge, and consequently, perceive less risk associated with EVs than do people from smaller cities. Given that the lower level of perceived risk of EVs may facilitate EV adoption (Qian and Yin, 2017), Chinese consumers in big cities may be more likely to adopt EVs. Hence, we hypothesise the following effect of different sizes of cities on EV adoption.

H2: Consumers from bigger cities exhibit stronger preferences for EVs than those from smaller cities.

Considering H1 and H2, we argue that the 90s generation in big cities might be more receptive to innovative products, engage in more risk taking in their consumption process, and be more experienced in using digital technology than other consumers. Members of the 90s generation living in bigger cities are also more likely to develop stronger preferences for EVs than other consumers because of the high development level of EV charging infrastructure and higher level of EV knowledge associated with greater exposure to EVs. Therefore, we hypothesise the following interaction effect.

H3: 90s generation consumers from bigger cities exhibit stronger preferences for EVs than do other groups of consumers.

2.2. SP experiment

EVs remain in the early stage of the market diffusion process and most consumers (Song et al., 2020), particularly in the midsized and small cities of China, have not gained a great deal of experience in buying and using EVs. Therefore, we collected SP data based on a choice experiment (also known in the marketing field as a 'choice-based conjoint analysis') across different regions of China (Louviere et al., 2000). SP experiment has been widely used in marketing and transportation research to examine consumer choices and estimate demand for new products before they are widely available in the market, as well as to assess the potential effectiveness of policies before their implementation (Rao, 2014). In addition, SP experiment has been widely adopted to examine consumer preferences for EVs given the limited product availability and variety of EVs in the market (Liao et al., 2017).

2.2.1. Attributes and level

In our SP experiment, each participant was presented with four hypothetical choice scenarios. Each scenario consists of three different types of vehicles (i.e. ICEV, PHEV and BEV) specified on a range of attributes. We include the PHEV and the BEV in the choice set because they are the two types of EVs that are strongly supported by the Chinese Government for EV transition in China (State Council of the People's Republic of China, 2012). To complete the choice experiment, participants must choose their preferred vehicle from the three alternatives presented.

In the SP experiment, the attributes and levels of each alternative differ not only across the three alternatives but also for each scenario. Specifically, we select the key product, service and policy attributes (as discussed in Section 1) and determine their levels of variation according to previous literature and market practices (e.g. Helveston et al., 2015). Table 1 presents the list of attributes and their levels of values in our experiment.

Table 1: Attributes and Levels in SP Experiment

Attributes	**Value and Level**
Product Attributes	
ICEV purchase price (CNY10,000)	Specified by the respondents
PHEV purchase price (CNY10,000)	20% / 40% / 60% higher than similar sized ICEVs
BEV purchase price (CNY10,000)	30% / 50% / 70% higher than similar sized ICEVs
ICEV annual running cost (CNY10,000)	Market average level based on vehicle price level
PHEV annual running cost (CNY10,000)	40% / 50% / 60% of that of similar sized ICEVs
BEV annual running cost (CNY10,000)	10% / 25% / 40% of that of similar sized ICEVs
Driving range for ICEVs (after full refuelling)	600 km (petrol)
Driving range for PHEVs (after full refuelling and charging)	50 / 70/ 100 km (electricity) + 600 km (petrol)
Driving range for BEVs (after full charging)	80 /150 / 200 km (electricity)
Service Attributes	
Coverage of public petrol stations for ICEV	100% (all existing petrol stations)
Coverage of public fast charging or battery swapping stations for PHEVs and BEVs	10% / 40% / 70% of existing petrol stations
Petrol refuelling speed for ICEVs	5 min
Fast charging speed for PHEVs	10 / 20 / 30 min
Battery swapping or fast charging speed for BEVs	5 min (battery swapping) / 15 min (fast charging) / 30 min (fast charging)
Coverage of workplace/public slow charging posts for PHEVs and BEVs	10% / 40% / 70% of available parking spaces
Permission to install home slow charging post for PHEVs and BEVs	Yes / No
Charging speed in slow charging post for PHEVs	4 / 6 / 8 hours
Charging speed in slow charging post for BEVs	6 / 8 / 10 hours
Policies Attributes	
Government subsidy (CNY10,000) for ICEVs	No subsidy
Government subsidy (CNY10,000) for PHEVs	0% / 10% / 20% of purchase price
Government subsidy (CNY10,000) for BEVs	10% / 20% / 30% of purchase price
Vehicle licensing policy for ICEVs	Lottery-based licensing
Vehicle licensing policy for PHEVs	Free license immediately / Lottery-based licensing
Vehicle licensing policy for BEVs	Free license immediately / Lottery-based licensing

For product attributes, we include purchase price, running cost and driving range limit, which have been frequently examined in previous literature of EV adoption (e.g. Hoen and Koetse, 2014; Qian and Soopramanien, 2011; Eggers and Eggers, 2011). PHEVs and BEVs are typically more expensive to buy but their running cost is lower than a similar sized ICEV. Given the smaller battery size, PHEVs are assumed to be slightly cheaper to buy than BEVs but PHEVs also have a shorter electric driving range than BEVs. For the price levels and running cost, we applied the pivoting design technique to allow the values of the monetary attributes to be adapted according to the intended vehicle price range chosen by each respondent before the SP experiment (Qian and Soopramanien, 2011).

The service attributes are related to three types of EV charging service provision: public fast charging or battery swapping stations; workplace/public slow charging posts; and ability for home slow charging. Junquera et al. (2016) find that public charging stations can provide a fast charging service to recharge an EV within 30 minutes, while workplace/public charging posts and home charging posts usually have slow charging capability that takes several hours to recharge an EV. In addition, the geographic coverage of public fast charging stations is defined as a percentage of existing petrol stations in a given area (Tanaka et al., 2014), while the coverage of workplace/public slow charging posts is defined as the availability in the parking spaces of a given area (Qian and Soopramanien, 2011). Home charging capability is a dummy variable ("0" = No, "1" = Yes) that examines the potential effect of being able to charge the EV's battery at home.

For policy attributes, we include purchase subsidies and the policy on vehicle licensing because these are the two major means currently used to promote EV adoption in China. The study assumes that purchase subsidy for PHEVs or BEVs varies proportionally to the vehicle's purchase price. The study considers two types of vehicle licensing policies: free licensing immediately and lottery-based licensing. The lottery-based licensing process aims to decelerate the fast growth of ICEVs, while PHEVs and BEVs are currently either exempt from this lottery licensing process or have a higher chance of being licensed (Xing et al., 2016). Therefore, we assume that car buyers must go through the lottery process to obtain a license for ICEVs, but may be entitled to free licensing or are subject to lottery-based licensing to obtain a license for PHEVs or BEVs.

2.2.2. Design procedure

Considering all the attributes and their levels discussed above, there is a total of 38.2 million configured scenarios if we consider a full-factorial design. Thus, we employed the D-efficient design, which aims to minimise the D-error of the asymptotic variance–covariance (AVC) matrix for the design (Rose and Bliemer, 2009). Specifically, we adopted the D-optimal design in Qian et al. (2019), who produced 24 choice scenarios from the SP experiment design.

Given that 24 choice scenarios is still overwhelming for a single respondent, the online-survey system is used to randomly assign four choice scenarios to each respondent. Figure 1 depicts a sample choice scenario, which is similar to the choice scenarios used in Qian et al. (2019).

2.3.Measurements for EV evaluations

Existing studies on sustainable innovation usually argue that positive evaluations of functional, psychosocial and environmental attributes are particularly important for the adoption of sustainable innovation (Noppers et al., 2015). In addition, future aspiration has been found to be crucial in promoting the low-carbon transport future (Hickman et al., 2011). In this study, we also assess respondents' perceptions of these four variables (i.e. functional, environmental, psychosocial and future aspiration aspects of EVs). These evaluation questions were presented to respondents before the SP experiment to avoid the choice scenarios we present affecting the responses in the SP experiment. See the Appendix for the detail of the items used for these measurements.

To evaluate the perception of EV function, we develop a single-item measure asking, 'to what extent do you believe EVs have satisfying functional performance' (Schuitema et al., 2013). The environmental aspect of EVs mainly relates to their reduced carbon emissions (zero emissions for BEVs) when driving an EV (Simsekoglu, 2018). To evaluate the perception of EV environmental benefit, we develop a single-item measure asking, 'to what extent do you believe wide adoption of EVs has a positive impact on the environmental protection'.

Figure 1: A Sample Choice Scenario

Attributes		**Petrol Vehicle**	**Plug-in Hybrid Electric Vehicle (PHEV)**	**Battery Electric Vehicle (BEV)**
Product attributes	Purchase price	CNY80,000	CNY96,000	CNY104,000
	Running cost	CNY20,000 per year	CNY12,000 per year	CNY5000 per year
	Driving range	600 km (petrol)	50 km (electricity) + 600 km (petrol)	200 km (electricity)
Service attributes	Coverage of petrol or public fast charging stations	100% (all existing petrol stations)	equivalent to 70% of existing petrol stations	equivalent to 70% of existing petrol stations
	Service speed in petrol or public fast charging station	5 min (petrol refuelling)	10 min (fast charging)	30 min (fast charging)
	Coverage of workplace/ public slow charging posts	NA	70% of available parking spaces	70% of available parking spaces
	Permission to install home charging post	NA	No, not permitted	No, not permitted
	Charging speed in slow charging post	NA	4 hours (slow charging)	8 hours (slow charging)
Policy attributes	Government subsidy	No subsidy	No subsidy	CNY31,200 (30% of purchase price)
	Vehicle licensing policy	Lottery-based licensing	Free license immediately	Lottery-based licensing

Given the three vehicles described above, which one would you be most likely to adopt?

(A) Petrol Vehicle; (B) PHEV; (C) BEV

To evaluate the effect of the psychosocial aspect of EVs, we adapted the measures of Zhu et al. (2012), who examine Chinese consumers' psychological valuation of car ownership from the perspective of the following four aspects: success, control, necessary and modern. The corresponding items were used to measure the psychological effect of private car ownership, but were also adapted to relate specifically to the EV context in relation to adopting and owning EVs. The overall score of the psychosocial aspect for general cars or EVs is the average score of the four items. The psychological value of using EVs in the Chinese context is not yet clearly understood because EVs are still in the early stage of market penetration (Huang and Qian, 2018). It is therefore useful to examine the psychosocial value of EVs, which largely depends on the extent to which consumers perceive that EVs are psychosocially better than general cars. Thus, we measure consumers' perceptions of the psychosocial advantages of EVs by measuring the difference between consumers' perceptions of the psychosocial value of owning a general and owning an EV.

Further, consumers' aspirations relating to EVs in the future may play an important role in their decision to adopt a low-carbon innovation product (Geels and Verhees, 2011). That is, given that a fully integrated EV transport system has not yet been well established in China, the consumer must be able to imagine or believe in such a system as a possible or likely future before deciding to buy an EV (Bergman et al., 2017). To evaluate whether consumers foresee a prosperous future for EVs, we included the following two items: The first one is "in 2045, my family and I will move around in a new, green mobility system." The second one is "in 2045, I see myself and my family moving around using electric vehicles." The overall score for future aspiration relating to EVs is the average score of these two items.

2.4. Demographics and individual characteristics

We also asked questions to obtain information on demographic and individual characteristics, including respondent's gender, age, education level, household income in 2017, car driving experience, EV knowledge level, car knowledge level, household size (i.e. number of people in their household), and household car ownership level.

2.5. Data collection

We established and implemented the SP experiment and other questions in an online questionnaire hosted by an internet-based survey platform. A pilot survey was conducted in early 2017 to test the survey platform and improve the readability of the questionnaire design. To prepare for the nationwide data collection, we employed 46 university students as the survey assistants whose home cities were located in 24 automobile-market clusters across China, as identified by McKinsey(Wang et al., 2012). Further, we consider the population statistics on the United Nations World Urbanization Prospects to focus on cities with at least 300,000 urban residents (United Nations, 2014).

To ensure a high response rate, the 46 survey assistants contacted and invited their friends and families to subscribe to the survey six months before our data collection. We applied a quota sampling approach, and the expected number of recruited participants in each automobile-market cluster was determined by the cluster's proportion of car market share in 2020, as predicted by McKinsey (Wang et al., 2012). A total number of 1282 participants subscribed and agreed to join our subsequent survey. By recruiting participants from the 24 automobile clusters in mainland China,[3] our study obtained a wider sample coverage than the samples used in prior research conducted in this context (e.g. Helveston et al., 2015).

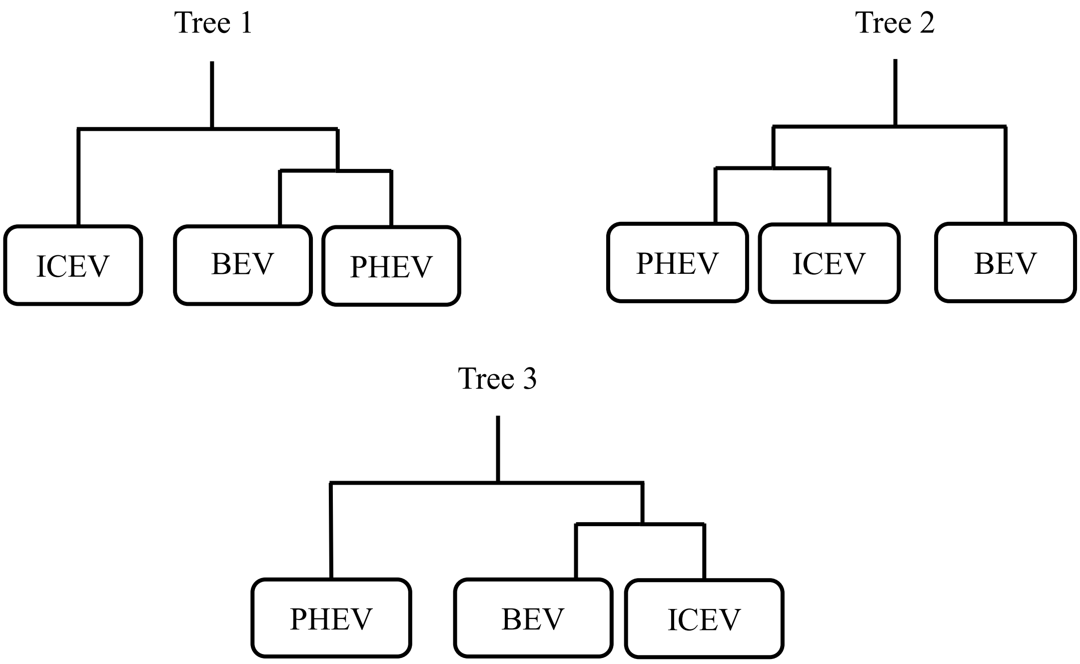
During the winter holiday of Chinese universities in January and February 2018, the research assistants returned to their home cities and sent an online link of the survey to the people who had previously subscribed inviting them to participate the online survey. Participants who encountered difficulties in understanding the questionnaire or accessing the internet were provided additional support. Among the 1282 survey subscribers, 989 successfully completed the survey without missing key questions, yielding a completion rate of 77.15%.

2.6. NL modelling

We apply discrete choice modelling approach, which is based on the utility maximisation theory (Train, 2009), to examine consumer preferences for EVs. We formulate the utility for each individual and each alternative (i.e. BEV, PHEV and ICEV) as a linear function incorporating the SP experiment attributes (as listed in Table 1), as well as the individual characteristics interacting with alternative specific constants (ASCs) of the PHEV and the BEV.

When estimating the discrete choice models, the multinomial logit (MNL) model is often used, principally because of its simplicity.[4] However, the independence of irrelevant alternatives (IIA) property of the MNL model assumes that all the alternatives are independent of each other, and thus the MNL model cannot account for heterogeneous substitution preferences between EVs and ICEVs (Qian and Soopramanien, 2015). As an extension of the MNL model, the NL model is not constrained by the IIA property of the MNL because it groups alternatives that share seemingly similar facets into nest(s). NL is often used by researchers to account for the potential correlation between alternatives (Ben-Akiva and Lerman, 1985) and its ability to capture substitution patterns among different alternatives (Train, 2009). Therefore, we apply the NL model to examine consumers' SPs for EVs.

Figure 2: Three Tree Structures for NL Models



Specifically, we consider and test three tree structures (see Figure 2) that illustrate three types of possible correlation among the alternatives. By assuming that there is correlation between two alternatives in each case, each tree structure in Figure 2 has two alternatives within a branch. We fit three NL models corresponding to these three tree structures and then identify the most appropriate choice structure by examining their corresponding inclusive value (IV) parameters. In NL modelling, the IV parameter is a key indicator used to judge the empirical validity of the nested choice structure. More specifically, the IV parameter must fall between 0 and 1 to ensure the model's consistency with utility maximisation (Train, 2009, pp. 83–84).

3. Results

3.1. Sample description

Table 2 demonstrates that our respondents are from different tiers of residential cities. Specifically, 17.2% of the respondents lived in first-tier and second-tier cities (categorised as big cities), 67% of the respondents lived in the third-tier cities (categorised as midsized cities), and the remaining 15.8% respondents lived in fourth-tier and fifth-tier cities (categorised as small cities). It is important to note that we oversampled respondents from third-tier cities compared with the actual population data.[5] Therefore, in the discrete choice modelling analysis we reweigh the sample data according to the actual proportion of the urban population of each tier of China's cities to enhance the representativeness of our sample. In doing so, we follow the United Nations (2014) historical and predicted urban population data for each Chinese city with a population of 300,000 or more. In relation to age distribution, approximately 45.5% of participants are aged between 18 and 29 years old, and thus belong to the 90s generation and are usually considered a promising market segment of new car buyers in China. Our sample also has a large group of consumers in the pre-90s generation, with 54.5% of respondents aged 30 and older. In relation to the gender of the respondents, we have slightly more female than male participants. As with many empirical studies in the Chinese context (e.g. Qian and Yin, 2017), we have a high proportion of university-educated respondents (66.1% with bachelor or postgraduate degree), car users (68.3% with at least one year of car use experience), and car-owning households (86.6% owning at least one car in their household). In relation to household income, this demographic characteristic ranges from 22.0% of households earning less than CNY100,000 in 2017 (approximately USD15,150) to 26.8% of households having an annual income of more than CNY300,000 in 2017 (approximately USD45,450). In addition, 44.9% of respondents reported a medium level of self-reported EV knowledge (indicated by a '3' on a 5-point scale) and less than 10% had extremely high or extremely low knowledge about EVs (indicated by a '1' or '5' on a 5-point scale).

3.2.Results of discrete choice modelling

With the SP data, we first establish a baseline NL model with SP experiment attributes and individual characteristics, without considering the generational and city-size variables. In the next stage of the empirical analysis, we extend the baseline model in three ways by adding (1) the generational variables into the baseline model; (2) the city-size variables into the baseline model; (3) the interactions of generational variables and city-size variables into the baseline model. The estimation results of the baseline and three extended NL models are presented in Table 3. Across these four models, the IV parameter corresponding to Tree Structure 1 in Figure 2 (which has PHEV and BEV in the same branch) is consistently between 0 and 1, and importantly, it is different from both 0 and 1 at the 5% significance level. This implies that consumers perceive a high level of similarity between these two types of EVs. Therefore, we focus on this choice structure to discuss the results in the baseline model and then the specific effects of the generational variables and the city-size variables, and their interactions in the extended models.

3.2.1. Results of the baseline NL model

Based on Tree Structure 1, the baseline NL model (i.e. NL1 in Table 3) achieves the log-likelihood value of −3893.52 at convergence, and the likelihood ratio test indicates that this NL mode is significantly better than the MNL model ($\chi^2 = 6.70$, df = 1, $p < 0.01$). All of the estimated parameters of functional, service and policy attributes included in the SP experiment have the expected signs. That is, we find that Chinese consumers strongly prefer cars with a lower purchase price, lower running cost and longer driving range. However, we do notice a large difference in the coefficient magnitudes of the two monetary attributes, which highlights that Chinese consumers perceive savings from the annual running cost to be more important than a lower purchase price.

Table 2: Demographic Characteristics of Sample

Sample Characteristics		Unweighted Sample	Weighted Sample*
Sample size		989	989
Tiers of cities[a]	First tier (big city)	12.6%	18.5%
	Second tier (big city)	4.6%	13.5%
	Third tier (midsized city)	67.0%	35.9%
	Fourth tier (small city)	6.5%	21.2%
	Fifth tier (small city)	9.3%	10.9%
Age	18–29 (90s generation)	45.5%	45.7%
	30–39 (pre-90s generation)	6.5%	9.1%
	40–49 (pre-90s generation)	33.6%	29.8%
	50–60 (pre-90s generation)	12.3%	12.3%
	Over 60 (pre-90s generation)	2.1%	3.1%
Gender	Male	38.6%	38.6%
	Female	61.4%	61.4%
Highest education level	Below senior high school	5.7%	5.3%
	Senior high school	14.2%	13.2%
	Junior college	14.2%	15.2%
	Bachelor	59.4%	58.7%
	Postgraduate	6.7%	7.6%
Car use experience (year)	No experience	31.7%	33.7%
	Less than 1	19.4%	17.0%
	1–3	14.2%	15.1%
	4–6	8.8%	7.9%
	7–9	7.9%	7.7%
	10 or longer	18.0%	18.7%
Number of private cars in household	0	13.4%	15.5%
	1	52.7%	54.0%
	2	27.7%	24.9%
	More than 2	6.2%	5.6%
Annual household income (in 2017)	Less than CNY100,000 (USD14.49 thousand)	22.0%	22.2%
	Between CNY100,000 and 200,000 (USD28.98 thousand)	30.5%	30.7%
	Between CNY200,000 and 300,000 (USD43.47 thousand)	20.4%	19.5%
	Between CNY300,00 and 400,000 (USD57.96 thousand)	11.8%	13.1%
	More than CNY400,000	15.0%	14.5%
Level of self-reported EV knowledge (five-point scale)	1 (never heard)	5.8%	6.5%
	2	27.8%	28.2%
	3	44.9%	44.3%
	4	18.2%	17.6%
	5 (very acknowledged)	3.3%	3.4%

[*] Reweighting according to the actual proportion of the urban population in each tier of China's cities, following the United Nations (2014) historical and predicted urban population data for each city of at least 300,000 residents.

[a] The classification of city tiers in China follows the recent national standard from the State Council of the People's Republic of China (http://www.gov.cn/zhengce/content/2014-11/20/content_9225.htm)

Table 3: Estimation Results for the Baseline and Extended NL Models

Variables	**NL1: Baseline**	**NL2: Baseline + Generation**	**NL3: Baseline + City**	**NL4: Baseline + Generation*City**
Alternative Specific Constants (ASCs) [a]				
For BEV	−0.746	−0.725	−1.290	−1.015
For PHEV	0.069	0.137	−0.609	−0.602
Product, Service and Policy Attributes				
Vehicle purchase price (CNY10,000)	−0.034 ***	−0.034 ***	−0.033 ***	−0.033 ***
Annual running cost (CNY10,000)	−0.239 ***	−0.239 ***	−0.237 ***	−0.239 ***
Driving range after full charging or refuelling (km)	0.002 ***	0.002 ***	0.002 ***	0.002 ***
Coverage of public fast charging or battery swapping stations (%)	−0.001	−0.001	−0.000	−0.000
Service speed in public fast charging or battery swapping stations (mins)	−0.007 †	−0.007 †	−0.007 *	−0.007 *
Coverage of workplace/public slow charging posts (%)	0.003	0.003	0.003	0.003
Permission to install home slow charging post	0.422 *	0.425 *	0.381 *	0.383 *
Charging speed in slow charging posts (hours)	−0.008	−0.009	−0.007	−0.007
Government subsidy (CNY10,000)	0.028 **	0.028 **	0.029 **	0.028 **
Free and immediate vehicle licensing [b]	0.382 ***	0.382 ***	0.381 ***	0.382 ***
Individual Evaluations for EVs Interacted with ASCs				
Functional evaluation for EVs * PHEVs	0.264 *	0.274 *	0.212 *	0.216 *
Functional evaluation for EVs * BEVs	0.289 *	0.301 *	0.244 *	0.252 *
Environmental evaluation for EVs * PHEVs	0.046	0.050	0.035	0.033
Environmental evaluation for EVs * BEVs	0.052	0.051	0.041	0.032
Psychosocial advantage for EVs * PHEVs	0.617 *	0.641 *	0.539 *	0.548 *
Psychosocial advantage for EVs * BEVs	0.741 **	0.773 **	0.663 **	0.679 **
Future aspiration evaluation for EVs * PHEVs	0.186 †	0.193 †	0.154 †	0.156 †
Future aspiration evaluation for EVs * BEVs	0.222 *	0.235 *	0.195 *	0.203 *
Demographic Factors Interacted with ASCs				
Male * PHEVs	−0.701 *	−0.731 *	−0.600 *	−0.605 *
Male * BEVs	−0.885 *	−0.917 *	−0.783 *	−0.786 *
Highest education level * PHEVs	0.245 †	0.272 †	0.266 *	0.272 *
Highest education level * BEVs	0.274 *	0.246 †	0.283 *	0.237 †
Number of cars in the household * PHEVs	0.328 †	0.347 †	0.320 †	0.328 †
Number of cars in the household * BEVs	0.379 *	0.376 †	0.369 *	0.354 *
Household size * PHEVs	0.198	0.207	0.145	0.149
Household size * BEVs	0.327 *	0.339 *	0.279 *	0.290 *
Number of children in the household * PHEVs	0.027	0.020	0.012	0.018
Number of children in the household * BEVs	−0.139	−0.128	−0.153	−0.124
Car driving experience * PHEVs	−0.112 †	−0.127 †	−0.108 †	−0.113 †
Car driving experience * BEVs	−0.093	−0.061	−0.087	−0.046
Preferred price range for EVs * PHEVs	−1.249	−1.329	−0.996	−1.022
Preferred price range for EVs * BEVs	−1.179	−1.257	−0.944	−0.966
Self-reported EV knowledge * PHEVs [c]	−0.228	−0.235	−0.220	−0.233
Self-reported EV knowledge * BEVs [c]	−0.212	−0.233	−0.197	−0.236
90s generation * PHEVs [d]		−0.082		
90s generation * BEVs [d]		0.236		
Living in small city * PHEVs [e]			0.986 *	
Living in small city * BEVs [e]			0.749 †	
Living in midsized city * PHEVs [e]			0.485 *	
Living in midsized city * BEVs [e]			0.321	
90s generation living in small city * PHEVs [f]				1.242 *
90s generation living in small city * BEVs [f]				1.026 *
Pre-90s generation living in small city * PHEVs [f]				0.860 *
Pre-90s generation living in small city * BEVs [f]				0.249

Variables	NL1: Baseline	NL2: Baseline + Generation	NL3: Baseline + City	NL4: Baseline + Generation*City
90s generation living in midsized city * PHEVs [f]				0.310
90s generation living in midsized city * BEVs [f]				0.038
Pre-90s generation living in midsized city * PHEVs [f]				0.630 †
Pre-90s generation living in midsized city * BEVs [f]				0.195
Pre-90s generation living in big city * PHEVs [f]				0.002
Pre-90s generation living in big city * BEVs [f]				−0.391
Number of parameters	37	39	41	47
Log-likelihood value at convergence	−3893.52	−3889.45	−3879.93	−3873.10
95% CI of IV parameter for the nest with BEV and PHEV	(0.102, 0.794)	(0.095, 0.766)	(0.125, 0.871)	(0.126, 0.859)
McFadden pseudo R-squared	0.166	0.167	0.169	0.171
Likelihood ratio test against the NL1 model [d]		8.14 *	27.18 ***	40.84 ***

Note: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, † $p < 0.1$.

[a] ICEV is the reference alternative for ASCs.

[b] Lottery process for vehicle licensing as the base category.

[c] Dummy variable that denotes self-reported EV knowledge greater than 3 out of 5 (5-point scale).

[d] pre-90s generation as the base category.

[e] Living in big cities as the base category.

[f] 90s generation living in big cities as the base category.

For the service attributes, we find that fast charging/battery swapping speed and home charging capability are crucial for Chinese consumers' choice of EVs. Meanwhile, the coverage levels of fast charging or battery swapping service, slow charging service, and slow charging speed are not considered important by Chinese consumers. Considering the effects of all service attributes, our analysis indicates that Chinese consumers generally prefer to charge their EVs at home given that this provides exclusive access as opposed to competing for and sharing public service provisions with other EV users.

Both government subsidy and free licensing policy are significant with positive signs. Notably, while previous empirical studies have obtained mixed results for the effect of prioritised licensing policy on EV adoption in China (e.g. Huang and Qian, 2018), our results provide support for the effectiveness of this policy in EV adoption. We contend that this is because unlike previous research, we use data from a nationwide study in China.

As one of the contributions of this study, we examine the effect of respondents' evaluations of the functional, environmental and psychosocial aspects of EVs, as well as their future aspirations relating to EVs through their interactions with the ASCs of BEVs and PHEVs. The higher evaluation of the functional aspect of EVs is strongly and positively associated with preference for both types of EVs, while the higher evaluation on the environmental aspect of EVs has a positive but insignificant effect on EV preference, which implies that environmental concerns are not necessarily a driver of EV adoption in China (Li et al., 2017). In addition, we find that the higher evaluation of psychosocial advantage of EVs has a positive and significant effect on preference for EVs, and that its effect for BEVs is stronger than its effect for PHEVs, highlighting the crucial role of the perception of psychosocial advantage of EVs that has been overlooked by previous studies. Finally, the future aspirations aspect of EVs, which evaluates the effect of consumer's aspirations relating to the EV ecosystem in the future, is found to positively affect preference for both types of EVs. This provides empirical evidence to support the argument of Bergman et al. (2017) that consumers who imagine a prosperous future for EVs may allow this image to guide their positive preference for EVs to avoid cognitive dissonance. Surprisingly, the effect size of future aspirations relating to EVs is almost as large as that of the functional aspect. This implies the importance of not only functional aspects of EVs but also of consumers' perception of the importance of the role that will be played by EVs in their future.

For the effects of the demographic variables, we find that consumers who are female, better educated, and living in bigger households have stronger preference for EVs, and particularly BEVs. In addition, we find that consumers whose household has more cars are more likely to choose both types of EVs, which means that EVs are less likely to be considered the first car for Chinese consumers (Yang et al., 2017). In addition, we note that more car driving experience is negatively related to preference for a PHEV at the 10% significance level, possibly because of the technical complexity of PHEVs, to which experienced ICEV drivers find difficulty adapting (Rezvani et al., 2015). We use respondents' intended price range for next car purchase as a proxy for their income (Hackbarth and Madlener, 2013), but do not find it significant in influencing the choice of BEV or PHEV. In addition, we do not find a strong association between respondents' self-reported EV knowledge and their preference for EVs.

3.2.2. Preference heterogeneity across generations and cities

To examine the EV preference heterogeneity across generations and different sizes of cities in China, we extend the baseline NL model by adding the generation variables, the city-size variables, and their interactions step-by-step. The results are presented in the NL2 (generation variables), NL3 (city-size variables) and NL4 (interactions between generation and city-size variables) models of Table 3.

In NL2, to examine the generational effect on preference for EVs, we introduce a dummy variable for 90s generation (where the reference category is pre-90s generation) to interact with the ASCs of the PHEV and BEV respectively. As presented in Table 3, the NL2 model yields a log-likelihood value of −3889.45, which is significantly better than that of the baseline model according to a likelihood ratio test ($\chi^2 = 8.14$, df = 2, $p < 0.05$). However, in relation to the generational effect, we find that consumers in the 90s generation do not differ significantly from those in the pre-90s generation in relation to preferences for both types of EVs ($p > 0.05$). This means that at the national level, there is no generational difference in preference for EVs in China. Therefore, H1 is not supported, even despite the fact that it is typically presumed that younger consumers are more likely to adopt innovative products (Accenture Research Center, 2018) and more aware and conscious of environmental problems and sustainability issues (Gurtner and Soyez, 2016).

The NL3 model investigates the effects of different sizes of cities on preference for EVs by interacting two dummy variables for small and midsized cities (big cities as the reference category) with the ASCs for PHEV and BEV. The NL3 model has a log-likelihood value of −3879.93, and the likelihood ratio test shows that the NL3 significantly outperforms the baseline model ($\chi^2 = 27.18$, df = 4, $p < 0.001$), which indicates the substantial power of the city-size variables to improve the model performance. More specifically, consumers from "small cities" are most likely to adopt PHEVs, given the positive and significant interaction effect ($\beta = 0.986$, $p < 0.05$), followed by those from "midsized cities" who also present positive preferences for PHEVs ($\beta = 0.485$, $p < 0.05$), while consumers from "big cities" show least preferences for PHEVs. Notably, this result is different from that of Huang and Qian (2018), who find that consumers from the third-tier cities (i.e. midsized cities) are less open to EVs than those from second-tier cities (i.e. big cities); however, their study was conducted in one region of China (south Jiangsu). It is worth emphasising that the coefficient magnitude of 'small city * PHEVs' is more than twice that of 'midsized city * PHEVs', which clearly indicates an ordered pattern of preference for PHEVs across different sizes of cities. That is, consumers in small cities exhibit the strongest preference for PHEVs, followed by those from the midsized cities, and then those from big cities. For preference for BEVs, consumers from both small and midsized cities present a positive preference for BEVs (with those in big cities as the reference). The interaction effect between small cities and BEVs is significant at the 10% level ($\beta = 0.749$, $p < 0.1$), while the interaction between midsized cities and BEVs is insignificant. To summarise, our results on the effect of different sizes of cities clearly demonstrate that consumers in smaller cities in China have stronger preferences for EVs than those from the bigger cities in China, and thus H2 is rejected.

In NL4 model, we examine the interactions of the generation effects and the city-size effects to test H3. In this model, consumers from the 90s generation and who live in big cities represent the reference group. The NL4 yields a log-likelihood value of −3873.10. The likelihood ratio test shows that this model significantly outperforms the baseline model ($\chi^2 = 40.84$, df = 10, $p < 0.001$), implying that these two effects jointly contribute to a better explanation of the choice that consumers make between electric and petrol fuel cars. For the preference for PHEVs, the results show that the 90s generation from the small cities are most likely to adopt PHEVs ($\beta = 1.242$, $p < 0.05$), followed by the pre-90s generation in the small cities ($\beta = 0.860$, $p < 0.05$), and then the pre-90s generation from the midsized cities ($\beta = 0.630$, $p < 0.10$). In comparison, consumer preferences for PHEVs among the 90s generation in the midsized cities and pre-90s generation in the big cities do not differ significantly from that of 90s generation in big cities. As for consumer preferences for BEVs, the results show that the 90s generation living in small cities has a significantly stronger preference for BEVs ($\beta = 1.026$, $p < 0.05$) than those of the 90s generation consumers in big cities, while consumers in other generation-city segments do not have different preferences for BEVs than those of the 90s generation consumers in big cities. As consumers of the 90s generation living in big cities do not exhibit stronger preferences for PHEVs or BEVs than any other groups of consumers, H3 is rejected.

3.3. Further analyses across different generations and cities

To further explore the empirical results described above for preference heterogeneity (or homogeneity) across generations and tiers of cities, we conduct further analyses to compare respondents' evaluations of the functional, environmental, psychosocial, and future aspiration aspects of EVs across the generational and city-size dimensions, respectively. See Table 4 for the comparison results.

Table 4: Comparison of Subjective Evaluations of EVs across Generations and Cities

	Generational difference [c] (Diff = 90s generation – pre-90s generation)		City difference [d] (Diff = big/midsized cities – small cities)	
Four EV Evaluation Aspects [a]	Mean Diff	p-value	Mean Diff	p-value
Functional	−0.049	0.618	−0.282*	0.036
Environmental	−0.048	0.622	−0.261*	0.033
Psychosocial advantage of EVs over general cars [b]	−0.170†	0.066	−0.315*	0.013
Success	−0.316**	0.004	−0.404**	0.007
Control	−0.209†	0.052	−0.240	0.102
Necessary	−0.144	0.275	−0.265	0.142
Modern	−0.011	0.929	−0.351*	0.043
Future aspiration	−0.178†	0.055	−0.166	0.192
Green mobility in 2045	−0.211*	0.035	−0.170	0.182
EV ecosystem in 2045	−0.145	0.141	−0.162	0.229

Note: ** $p < 0.01$, * $p < 0.05$, † $p < 0.1$.
[a] Please refer to the Appendix for the measuring item of each aspect.
[b] The overall score of the psychosocial advantage of EVs is the average score of the four dimensions of the psychosocial advantage.
[c] Subsample size for 90s generation is 450 and for pre-90s generation is 539.
[d] We have 156 respondents from small cities and 833 respondents from big and midsized cities.

3.3.1. Comparison of 90s generation and pre-90s generation

We use independent sample t-tests to examine the statistical difference between the 90s generation and pre-90s generation in their evaluations of the functional, environmental, psychosocial and future aspiration aspects of EVs. Specifically, we do not find any significant difference between the two generations in the evaluations of these two generations of the functional or environmental aspects of EVs. Further, surprisingly, the 90s generation is more likely than the pre-90s generation to perceive that EVs have a psychosocial disadvantage over cars in general, as indicated by the negative coefficient significant at the 10% level (Diff = −0.170, $p = 0.066$). This finding is attributable to the intergenerational differences on the following two views: (1) owning EVs instead of general cars is a symbol of success in life (Diff = −0.316, $p < 0.01$) and (2) EVs make them feel more in control of their lives (Diff = −0.209, $p = 0.052$). Additionally, the comparison of the generational evaluations of the future aspiration aspect of EVs reveals that the 90s generation has less belief than the pre-90s generation that there will be a green mobility system in the future (Diff = −0.211, $p < 0.05$). Such comparisons further support the contention that the younger generation in China does not have stronger preferences for EVs than does the older generation.

3.3.2. Comparison of different sizes of cities

When comparing the effects between different sizes of cities, we combine the midsized and big cities and compare them against small cities in China. We find that respondents in small cities have a significantly higher evaluation of the functional (Diff = −0.282, $p = 0.036$) and environmental aspects of EVs (Diff = −0.261, $p = 0.033$) than those living in midsized or big cities. Moreover, compared with consumers in midsized and big cities, consumers in small cities perceive stronger psychosocial advantages of EVs, particularly in the success (Diff = −0.404, $p = 0.007$) and modern dimensions (Diff = −0.351, $p = 0.043$). We do not find a significant difference in the evaluations of the future aspiration aspect of EVs between respondents living in small cities and those living in midsized and big cities.

We also conduct analysis of variance (ANOVA) tests to examine the multi-group differences and patterns for the subjective evaluations relating to EVs across different sizes of cities. As shown in Figure 3, consumers in small cities generally have the highest mean value for every aspect of the subjective evaluations for EVs, followed by those from midsized cities, and then those from big cities. This pattern suggests that consumers in small cities are generally most favourable in their subjective evaluations of EVs. Moreover, in line with the *t*-test results discussed above, the ANOVA tests reveal statistically significant multi-group differences for the dimensions of functional ($F_{2,\ 986} = 6.513$, $p = 0.002$), environmental ($F_{2,\ 986} = 2.933$,

$p = 0.054$), psychosocial advantage of EVs over general cars ($F_{2, 986} = 3.615$, $p = 0.027$), and success ($F_{2, 986} = 3.996$, $p = 0.019$). Interestingly, the additional analyses also reveal significant multi-group differences for future aspiration ($F_{2, 986} = 3.416$, $p = 0.033$) and green mobility in 2045 ($F_{2, 986} = 4.491$, $p = 0.011$), while the independent sample *t*-test comparisons between small cities and midsized/big cities did not reveal these differences for these two variables. Thus, the ANOVA tests suggest that consumers in big cities are significantly less likely to believe in a prosperous future for green mobility than consumers in midsized and small cities.

To summarise, the results of the independent sample *t*-tests and the ANOVA analyses provide more in-depth additional empirical evidence to support one of the core arguments of this research, which is that where people live is more important than generational effects when examining consumer preference for EVs. That is, we find that consumers in smaller cities are more open to EVs principally because they have more positive evaluations on functional, environmental, and more significantly, psychosocial aspects of EVs than consumers in midsized and big cities.

4. Discussion

4.1. Specific contributions and key insights

This study contributes to the literature on the adoption of technologies that are crucial for regime changes with a focus on the adoption of EVs. The study makes five important contributions.

First, we contribute to the technology adoption literature focusing on the roles of generations and sizes of cities as important variables influencing the transition from one system to another. While some previous research suggests that younger generations of consumers (e.g. teenagers, Generation Y) tend to be more receptive to new technologies (e.g. Spero and Stone, 2004), other research argues that there is a lack of empirical support for this claim (Gabriel et al., 2004). Our study contributes to this debate, and in the context of the EV market in China, we find no significant differences in preferences between the 90s and pre-90s generations in China.

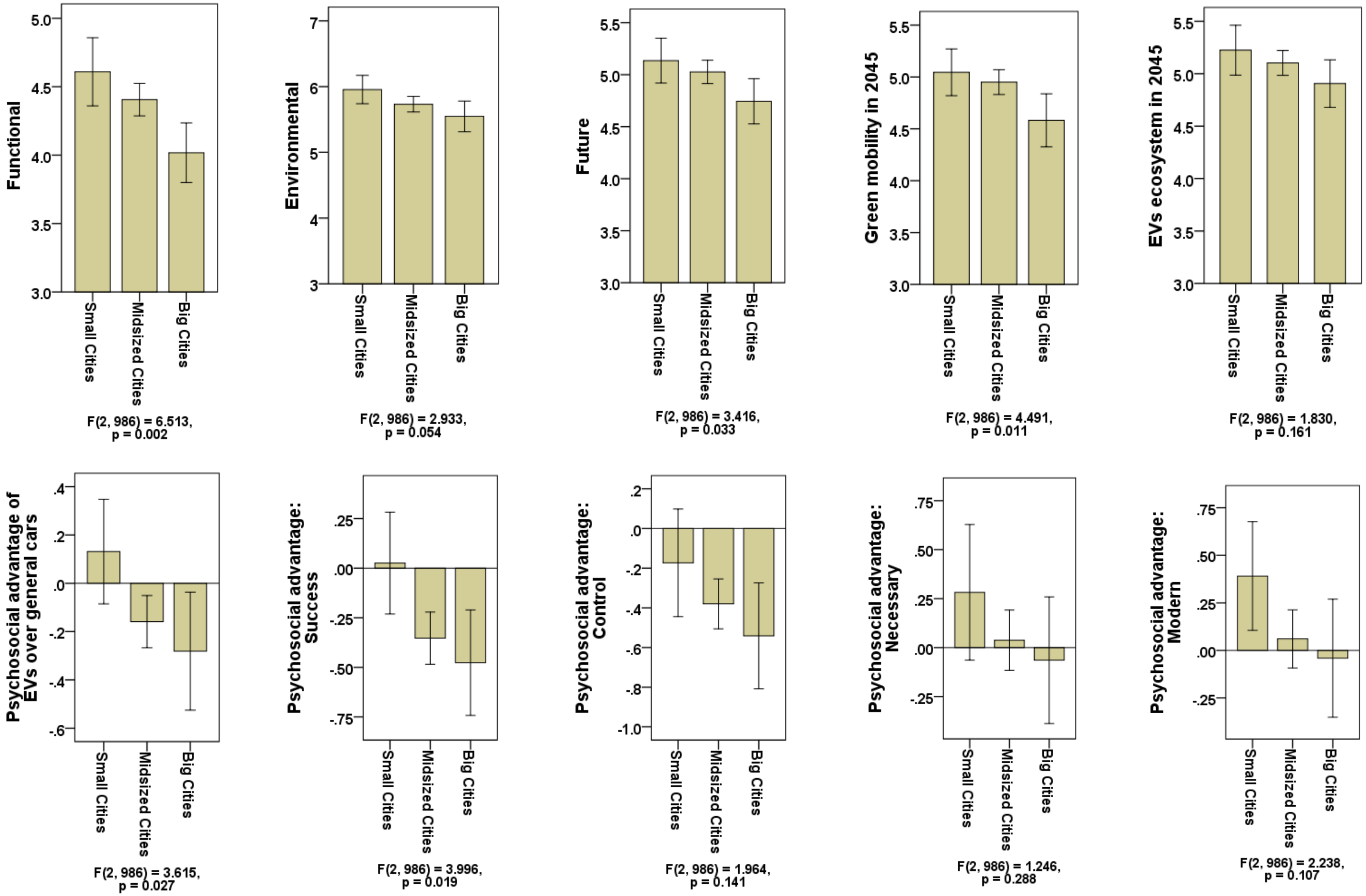


Figure 3: ANOVA Tests for Means of Subjective Evaluations for EVs across Consumers from Big, Midsized and Small Cities

Note: Error bar represents 95% confidence interval of the mean. F-test statistics and *p*-values are derived from the corresponding multi-group ANOVA tests.

We must also note here that little research attention has been paid to examining the influence of geographic variables to explain the differences in the adoption of new technologies. Only several empirical studies have found that consumers from bigger cities have earlier access to new innovative technologies and are more exposed to such innovations through peer influence, enabling them to acquire more knowledge on newer technologies than consumers from smaller cities (Schuitema et al., 2013). Prior research from Huang and Qian (2018) notes that consumers from second-tier cities in the south Jiangsu region of China are more open to EVs than those from the third-tier cities. In consideration of these findings, the stronger preferences for EVs of consumers living in smaller cities identified in our study might provide an important insight into understanding how the adoption of innovative technological products transfers from big cities and penetrates into smaller cities (Cui and Liu, 2000). In addition, existing studies tend to focus on one single demographic factor such as age to explain heterogeneity (e.g. Chéron and Kohlbacher, 2018). Thus, our research adds to the current knowledge on the effects of geographic variables on technological adoptions (e.g. private cars) (Zhu et al., 2012) by considering the interaction effect between generational and city-tier variables.

Second, we extend the literature on consumer preferences for EVs in China by collecting nationwide empirical data and examining the effects of two important but overlooked factors: generational effects and geographic effects. This examination is particularly valuable given that existing studies on EV adoption in China typically focus on respondents in either big cities or small regions (e.g. Helveston et al., 2015; Wang et al., 2018). The identified preference heterogeneity across different tiers of cities highlights the importance of locality in the transition of the economy towards EV mobility. In addition, in identifying this important variable, we also contribute to the literature on the geography of sustainable transition, which highlights the importance of examining spatial disparity (Hansen and Coenen, 2015). Further, our findings that consumers from smaller cities are more likely to adopt EVs demonstrate the market potential for EVs in smaller cities, and importantly, cast doubt on current government policies and EV-related infrastructure development in China, which have, so far, been targeted principally to first-tier cities. This also implies that in smaller cities, the younger generation of potential consumers represents a promising target market segment for EV market development in the long term, without the need to provide significant government subsidies, which are currently being gradually phased out in China.

Third, we enrich the literature on EV adoption by introducing consumers' subjective evaluations for EVs to explain consumer preference heterogeneity across generations and tiers of cities. We then compare the differences in these evaluations across different generations and tiers of cities. The combination of the SP experiment with consumers' subjective measures of their perception of the functional, environmental and psychosocial aspects of EVs is novel in explaining the heterogeneous preferences identified in the experiment. We find that consumers in small cities are more open to EV adoption because they place higher functional and environmental value on these vehicles, and more importantly because they see greater psychosocial advantages of these vehicles than those from midsized and big cities. Moreover, consistent with previous research (e.g. Noppers et al., 2015), we find the psychosocial aspect is a significant variable of influence in EVs adoption. This suggests that potential EV adopters in China may be driven by psychosocial factors as well as policy factors. Further, the psychosocial aspect (particularly in relation to the success and modern dimensions) is most prominently related to EV preferences among four aspects of the EV evaluations that we have examined in this study. This finding is largely consistent with Zhu et al. (2012) who highlight a higher psychological evaluation attached to car ownership in smaller cities than in first-tier ones.

Fourth, our research underlines the crucial role of consumers' future aspirations relating to the role of EVs in influencing their preferences to buy these cars. Although younger consumers are referred to as 'digital natives' and are presumed to be more open to new innovations such as EVs (Simsekoglu, 2018), we find that the 90s generation does not have a stronger preference for EVs than does the pre-90s generation. This may seem counterintuitive because we would expect the younger generation to advocate the use of EVs. However, this result highlights the need to interpret the findings in the specific market context of China. Our findings indicate that consumers in the 90s generation of China have weaker future aspirations related to EVs than do those from the older generation. This lack of aspirations related to EVs can be explained by the lower social status of the 90s generation in that young people in this group are in their early stage of career development and they usually place a higher importance on status consumption to lift their social status through buying expensive and publicly visible possessions (Zhu et al., 2012). EVs do not fulfil the role of affording status because they have not yet been widely symbolically recognised (Xue et al., 2013). Moreover, combining our findings regarding generational and geographic effects, we account for the weak preferences for EVs among 90s generation in bigger cities in two ways. First, the comparatively lower social status of the 90s generation will be most stark for those living in big cities. Second, while the sensitivity to current trends and tendency for fashionable display of success may be stronger in the 90s generation from bigger cities, such a display of success does not yet include EVs but rather a flashy, foreign ICEV with established status symbols. Thus, the prima facie greater interest of the 90s generation in digital technologies, which could one day include EVs but does not do so now, is currently overwhelmed and neutralised by city-based effects.

Fifth, this study makes an important contribution by complementing the existing literature on the future trajectory of EVs in the Chinese market. We note that the EV market in China began in first-tier cities, and the mature consumers in those big cities are assumed to be the typical buyers of EVs. However, the EV market in midsized and small cities now represents stronger growth potential given the higher growth rates in EV sales compared with the national average level in 2017 (Huang and Qian, 2018). According to our findings, the 90s generation in small cities is most open to EV adoption, followed by the pre-90s generation in small and midsized cities, while both generations in big cities are least open to EV adoption. Compared with young consumers who live in big cities under intense pressure and focus more on having materialistic success, their counterpart in small cities have less life pressures. Thus, young consumers in small cities are more likely to have 'dreams' about the future and can manifest their expected youthful technological optimism and spirit of 'venturesome consumption' (Bhidé, 2009). Therefore, following the start of EV transition among mature consumers in big cities in China, the future growth of the EV market in China may be generated by pre-90s generation consumers in midsized cities who exhibit strong preferences for PHEVs. This is particularly likely given that the largest urban population in China is in the midsized cities segment (United

Nations, 2014) and the fast development of transport infrastructure in these midsized cities. As EV technology becomes more diffused together with better infrastructure built in lower-tier cities, new market growth will then come more from smaller cities where potential EV adopters have higher evaluations of the functional, psychosocial, and future aspiration aspects of EVs. This strongly indicates that the growth of EV market in China will depend more on China's lower-tier cities.

4.2. Practical implications

We discuss below how the insights of this study can inform both government policy and business strategy.

4.2.1. Government policies

First, our results demonstrate that consumers of the 90s generation are less optimistic about the future of EVs, and the transition to EV mobility relies on this important segment of the future EV market. This indicates that government policy must consider how to better communicate EV policy and its strategic importance for the future of China's transport system to young people. More specifically, it is important for policy makers to educate young consumers better, possibly by disseminating more information about factors such as the sustainability of EVs on social media, which is becoming a learning platform for younger consumers in China. Given that we find that 90s generation consumers are not more inclined to EVs than the pre-90s generation, we also suggest that the Chinese governments should provide experiential opportunities for young consumers to use EVs. For example, they could implement programmes for EV sharing—particularly integrated with shared bikes to enable last-mile accessibility (Yin et al., 2018; Yin et al., 2019)—that target young people and ensure that they can have better experience of using EVs without ownership. Such innovative initiatives may help young people in China to learn about EVs and be more likely to form positive preferences for EVs.

Second, we find that consumers in small cities are more open to EVs than those from midsized and big cities, which indicates that the future growth of the EV market is in small cities.

However, it should also be noted that in these smaller cities, the relatively lower household income level and insufficient local charging infrastructure represent immediate major barriers for EV adoption. Thus, we recommend that local government authorities in small cities consider intensive collaboration with car manufacturers and encourage service providers to facilitate the EV market development in small cities. Further, our results reveal that consumers in small cities are more likely to believe that EVs have satisfying functional performance. Thus, it is important to not only contextualise the government policies in different sizes of cities, but also encourage car makers to design and produce EV models that are tailored to meet the needs and preferences of consumers in these specific markets. For example, local governments in China may promote specific models of EVs that are more suitable for local road and parking conditions, which can be achieved through collaboration with local car manufacturers to design and develop new offers for potential car buyers in these areas.

Third, our findings indicate the importance of home charging capability for EVs. However, many Chinese households do not have a dedicated parking space at home or are prohibited to install their own charging facilities (Qian et al., 2019). Therefore, local governments should improve the urban planning of residential compounds and work closely with property management firms to support the installation of home charging facilities for EVs. In particular, given that we find that consumers in small cities have stronger preferences for EVs than do those in midsized and big cities, it is important for local governments to prioritise EV infrastructure development in relation to better land-use planning and stronger support for installing charging facilities in smaller cities, where both home and public charging facilities are inadequate.

4.2.2. Managerial implications

First, our research highlights the significance of the tier of cities in the EV transition, and reveals that consumers in small tier cities have strong preferences for EVs. This calls for a shift in marketing strategies for car manufacturers. Although consumers in smaller cities exhibit stronger preferences for EVs, the word-of-mouth communication and exposure to EVs in such smaller cities may have been insufficient to generate a great deal of interest in EVs. Because consumers in small cities prefer cars that have a lower price (Huang and Qian, 2018), EV manufacturers may benefit from designing and producing more entry-level offerings (i.e. featuring more affordable EVs) to service this market segment.

Second, our findings on the pessimistic evaluations of younger consumers of the future of EVs and their value in their lifestyles indicate that these effects have somehow counteracted their initial interest in the concept of EVs. Because of the prominent importance of the psychosocial aspects of EVs in shaping consumer preferences for EVs, marketers must consider prioritising the symbolic attributes of EVs to attract younger consumers to adopt these vehicles. The significant psychosocial disadvantage of EVs as perceived by 90s generation is of concern in relation to the future prospects of such vehicles when we consider the importance of status identities desired by younger consumers.

Third, the significant difference in preference heterogeneity across different generational groups in different tiers of cities highlights the importance of differentiating marketing strategies for different geographic and generational groups, rather than merely relying one single dimension to inform marketing strategies. For example, we find that the 90s generation in small cities reports a stronger preference for EVs compared than all the other groups of consumers tested (e.g. the pre-90s generation in the same small cities). Thus, EV marketing strategists need to consider not only heterogeneity across different generations, but also how EV market characteristics differ across different tiers of cities in China. This two-dimensional heterogeneity also provides EV manufacturers insight into the future transition path of EVs in China. More specifically, while car manufacturers may believe that the market potential for EVs in the Chinese car market is greater in mature consumers in first-tier cities, our findings indicate that car manufacturers should consider the market potential of the 90s generation in smaller cities. For example, in the city of Liuzhou, a midsized city in southwest China, the market share of EVs reached 20% in 2018, which was largely attributed to the introduction of a small and more affordable (priced at approximately CNY40,000) EV model (the Baojun E100) that targeted young consumers.[6] The case of Liuzhou collaborates our empirical findings and demonstrates the possibility of the successful marketing of EVs to younger consumers in smaller cities in China.

5. Conclusions and Directions for Future Research

This study explores heterogeneity in consumer preferences for EVs across different generations and in different city sizes in China. Our results demonstrate that the geographic effect, which is captured by the sizes of the cities where consumers live, is more important than the generational effect in explaining heterogeneous consumer preferences for EVs in China. Specifically, consumers in smaller cities have stronger preferences for EVs and younger consumers in these smaller cities are the group that is most open to EV adoption. We also compare consumers' evaluations on the functional, environmental, psychosocial and perception of the future prospects of EVs to explain the heterogeneity in EV preferences.

We contribute to the literature by analysing the roles of the differences in generations and city sizes in the transition to ownership and usage of EVs. We extend the literature on consumer preferences for EVs in China by collecting and analysing nationwide empirical data, in particular by considering consumers' subjective evaluations of EVs and their future aspirations related to EVs. Thus, we demonstrate how these variables differ between generations and/or across different city sizes, providing new insights into the heterogeneous nature and trajectory of EV diffusion in China. Our study also provides several key practical implications for policy makers and business practitioners that are specific to this study's contributions. That is, we demonstrate the importance of educating younger consumers, contextualizing marketing strategies, and that the future of EVs may lie in developing the market in smaller cities through collaboration among car manufacturers, service providers and local governments.

This study has some limitations that must be acknowledged, and they also suggest avenues for future research. First, we collected cross-sectional data, which cannot capture evolution of preferences over time (Qian and Soopramanien, 2015). Future research could collect panel data and conduct a longitudinal analysis to explore dynamics in consumer preferences for EVs. The combination of both SP and revealed preference data can be another direction for future research to overcome the limitations associated with the hypothetical choices of SP experiment. Second, we examine the SPs for EVs based on choice-based conjoint analysis that consists of hypothetical scenarios. Future research could collect actual sales data of EVs over time and analyse the revealed preferences. The integration of data on stated and revealed preferences can generate better and more accurate insights into consumer behaviour in the EV market (Axsen et al., 2009). Third, although the city-size and generational factors examined in this study provide a new perspective for understanding the preference heterogeneity for EVs, we recognise that the dimension of city tiers may not fully capture all the aspects of market heterogeneity in the Chinese EV market. Future research could examine alternative dimensions of preference heterogeneity such as climate and air pollution levels across different cities in China to explore and reveal the potential of the Chinese EV market.

We acknowledge that our research is specific to the context of China. However, we hope that, through our work, other researchers will replicate similar analyses in other markets to gain valuable insights into the adoption of new products by applying spatial and demographic analyses. The size and diversity of markets such as Brazil and the United States make this type of analysis useful in those contexts. Data from smaller countries also show regional disparity in the adoption of EVs, which means that the type of analysis conducted in this study might also be useful in these smaller countries.

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Notes

1. The State Council of the People's Republic of China (2014) categorises Chinese cities into the following five classes based on urban population: first-tier city, over 10 million urban population; second-tier city, 5–10 million urban population; third-tier city, 1–5 million urban population; fourth-tier city, 0.5–1 million urban population; fifth-tier city, less than 0.5 million urban population.

2. The 25 pilot cities (tiers presented in the parentheses) proposed in 2010 are Beijing (1), Shanghai (1), Chongqing (1), Changchun (2), Dalian (3), Hangzhou (2), Jinan (3), Wuhan (2), Shenzhen (1), Hefei (3), Changsha (2), Kunming (3), Nanchang (3), Tianjin (1), Haikou (3), Zhengzhou (2), Xiamen (3), Suzhou (2), Tangshan (3), Guangzhou (1), Shenyang (2), Huhehaote (3), Chengdu (2), Nantong (3), and Xiangfan (3).

3. A cluster map of data collection can be found in Qian and Yin (2017). We notice that in Wang et al. (2012), some clusters consist of two or more provinces that have cross-province homogeneity, while one province can be treated as two market clusters because of the heterogeneity within the province. This study recruited participants from 29 of the 31 provinces of mainland China. We did not collect data from Ningxia Province or Qinghai Province, but we did collect data from Gansu Province which forms the Guanzhong Cluster together with Ningxia and Qinghai Provinces (Wang et al., 2012).

4. It is also possible that the alternatives are truly independent of each other and we do test this possibility by examining the validity of the NL models.

5. According to the United Nations (2014), China has 398 cities that have 300,000 urban residents or more. The percentages of urban population in different tiers of cities in China are as follows: 18.5% (first tier), 13.5% (second tier), 35.9% (third tier), 21.2% (fourth tier), and 10.9% (fifth tier).

6. See news about the Liuzhou Model at https://theicct.org/blog/staff/liuzhou-new-model-transition-electric-vehicles.

Appendix: List of Subjective Evaluation Survey Questions and Item Coding

Variables	**Items**	**Scales**
EV functional aspect	I believe EVs have satisfying functional performance.	7-point Likert scale
EV environmental aspect	I believe wide adoption of EVs has a positive impact on environmental protection.	(1 = strongly disagree; 7 = strongly agree)
Psychosocial aspect for cars		
Success	A private car is a symbol of my success in life.	7-point Likert scale
Control	A private car makes me feel more in control of my life.	(1 = strongly disagree;
Necessary	Having a car will be necessary in the future.	7 = strongly agree)
Modern	A car is a symbol of modern life.	
Psychosocial aspect of EVs		
Success	An EV is a symbol of my success in life.	7-point Likert scale
Control	An EV makes me feel more in control of my life.	(1 = strongly disagree;
Necessary	Having an EV will be necessary in the future.	7 = strongly agree)
Modern	An EV is a symbol of modern life.	
Future aspiration aspect of EVs		
Green mobility in 2045	In 2045, my family and I will move around in a new, green mobility system.	7-point Likert scale (1 = strongly disagree;
EV ecosystem in 2045	In 2045, I see myself and my family moving around using electric vehicles.	7 = strongly agree)