Dynamic Consumer Preferences for Electric Vehicles in China: A Longitudinal Approach

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Acknowledgement:

This research is supported by the National Natural Science Foundation of China (Grant No. 71973107 and 72202211), the Fundamental Research Funds for the Provincial Universities of Zhejiang (Grant Number: QRK22009) and the IBSS Development Fund (IBSSDF0320-17).

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Abstract

Sustainable innovations such as electric vehicles (EVs) are important means to address global environmental and energy sustainability challenges – one of the key agendas of current strategic government policy. Although EVs have gradually penetrated the market, existing research on consumer preferences for EVs is mostly based on cross-sectional analysis, without sufficient attention devoted to consumer preference changes over time. To fill this gap, this study proposes a longitudinal approach to extend the EV adoption research. Specifically, this study illustrates the value of studying consumer preferences for EVs from a dynamic perspective and focuses on changes in preference heterogeneity across different marketA segments over time. This study conducts three waves of stated preference experiments from 2017 to 2019 from a same group of respondents. The mixed logit analysis shows that, over these three years, Chinese consumers have become less sensitive to running cost but have been consistently valuing home charging capability and prioritized licensing for EVs. Furthermore, the perceived importance of the density of fast charging stations and overall preferences for EVs fluctuated over this period. Further analysis on preference heterogeneity finds that consumers in small cities were developing stronger preferences for battery EVs in 2018 and 2019 than in the base year of 2017, while those living in midsized and big cities did not present the preference change for battery EVs over the same period. Our study provides important managerial and policy implications for the diffusion of EVs, in particular with respect to specific insights obtained by taking a dynamic perspective to study consumer preferences for EVs.

Keywords: innovation adoption, dynamic preference, longitudinal approach, sustainable transition, electric vehicles

1. Introduction

The use of automobiles and, in particular, internal combustion engine vehicles (ICEVs) has created many societal and environmental problems (Urry, 2004). Transport accounts for 25% of worldwide carbon dioxide (CO_2) emissions, with this projected to increase to 50% by 2035 (McCollum et al., 2018). Electric vehicles (EVs) are currently considered among the most promising green technologies to help reduce carbon emissions (Sang and Bekhet, 2015) as well as other pollutants, such as NO_X and SO_2 (Li et al., 2019). Thus, many countries have been promoting research and development (R&D) and the marketisation of EVs (IEA, 2021). Taking China as an example, it started the pilot EV commercialisation programme in 2009 (Gong et al., 2013) and since 2016, it has been the largest single national market for EVs in the world (Huang et al., 2021a). In 2022, China reached a new sales record of 6.9 million EVs (including both full battery EVs and plug-in hybrid EVs), accounting for over 25% of new car sales in this market (People's Daily, 2023). Importantly, and this sets the context for the core research purpose of our paper, the development of the EV market is very dynamic, which is evidenced, for example, by the increasing number of new models from both major established car manufacturers and multiple new entrants to the automotive industry as well as supporting government policies. It is thus crucial for companies and policy makers to evaluate consumers' reaction to various changes in product/service attributes of EVs and policies over time.

Most existing studies on consumer preferences for EVs typically take a static perspective by collecting and analysing data from a cross-sectional survey (see the recent literature reviews in Liao et al., 2017, Rezvani et al., 2015 and Singh et al., 2020). Such studies can provide policy implications based on data at a specific time point (i.e., one snapshot of the market) but the insights gained do not enable us to capture how consumers are reacting over time. There are some exceptions and some recent studies have compared consumers' intentions to adopt EVs over time (Carley et al., 2019; Fan et al., 2020). These studies, however, commonly collected two waves of survey data, so that they cannot effectively account for the complex changes (such as the non-linearity) in consumer preferences for EVs over multiple time periods. Therefore, prior literature has paid insufficient attention to examining whether and how consumer preferences towards EVs and their attributes might change over multiple time periods and also how different segments in the market might react to EVs over time. To fill this research gap, our core research questions in this paper are as follows:

(1) How do consumer preferences for EVs and key attributes change over time?

(2) How does the preference for EVs change differently across different consumer segments over time?

To address these two research questions, we collected three waves of data by conducting the stated preference (SP) experiment three times from 2017 to 2019 among the same group of respondents whom we recruited in 2016. We then used discrete choice analysis, in particular mixed logit models, to examine how consumer preferences for EVs and their attributes changed across the three years. During the time of our data collection, the EV market share in China increased from 1.3% in 2016 to 4.3% in 2019 among new car sales (Souche and Baidu, 2023), and the Chinese government were gradually phasing out the EV purchase subsidies but launching the "Dual Credit policy" (its full name is "*Passenger Cars Company Average Fuel*

Consumption and New Energy Vehicle Credit Regulation") to drive all car makers to produce and sell more EVs as well as energy-saving cars in the market (Bloomberg News, 2019; Chen and He, 2022; Ou et al., 2018). Therefore, given the changing market environment caused by these factors, the three waves of SP experiment from the same group of respondents provide deeper insights whether and how consumers' preferences for EVs and their related policies might change over time. Such insights on the preference dynamics cannot be derived from a cross-sectional survey study and thus a dynamic perspective is more valuable for the policy makers as well as EV producers and charging service providers to make more effective policy and business decisions in the changing market environment.

Furthermore, we conducted additional analysis on the changes in consumer preferences for EVs across different tiers[1] of cities and different generations over three years. The reasons for these two additional levels of analysis are as follows. The Chinese EV market, from a regional analysis perspective, is highly diversified, with hundreds of cities at different stages of development (Huang and Qian, 2018). Though first-tier cities were positioned as the first target market for EVs, future growth potential can come more from midsized and small cities[2] (Huang et al., 2021a). This indicates the possibility that consumer preferences for EVs would change across different sized cities during the EV diffusion process and specifically that, over time, these changes are not similar across cities. The generational factor is also purported to be an important segmentation variable when studying demographic factors for future consumer

[1] The State Council of China categorises Chinese cities into five classes based on urban population: first-tier, over 10 million; second-tier, 5–10 million; third-tier, 1–5 million; fourth-tier, 0.5–1 million; and fifth-tier, less than 0.5 million. See http://www.gov.cn/zhengce/content/2014-11/20/content_9225.htm.

[2] We classify first- and second-tier cities as 'big cities', third-tier cities as 'midsized cities' and third-tier and smaller cities as 'small cities'.

market development in China. For example, consulting firms such as McKinsey have indicated the growing consumption power of the younger generations in China, such that the generation born in the 1990s will account for more than 20% of total consumption growth between 2017 and 2030 – higher than any other demographic segment (Baan et al., 2017). Therefore, it is important to evaluate whether and how their preferences for EVs are changing over time compared with the older consumer group.

Our contributions to the literature are threefold. First, we extend the literature on EV adoption by demonstrating the importance of employing a longitudinal approach to examine the potential changes in consumer preferences for EVs over multiple periods of time. Second, our longitudinal approach based on multi-wave data complements the existing applications of innovation diffusion theory (Rogers, 2003). Taking the EV market to illustrate, we show the value of examining the features of diffused innovations, such as relative advantage, complexity reduction and observability, from a dynamic perspective. Third, we add to the sustainable transition literature by revealing the diverse nature of the changes in consumers' preferences for EVs across different segments over time. Effectively, this paper does support the central tenet of the sustainable transition literature which argues that we ought to consider the complexities and heterogeneities that underlie sustainable transition – in this paper we consider consumer preference change from a segmental perspective and across time to illustrate.

The remainder of this paper is organised as follows. Section 2 reviews the existing literature on preferences for EVs and related theories that have been used to study adoption propensity of consumers for such products. Section 3 describes the research method and longitudinal data that we employ. Section 4 presents the analysis and discusses the results. The final section summarises the key results and discusses our theoretical contributions, managerial implications and future research directions.

2. Literature Review

In this section, we review the existing literature on consumers' preferences for EVs, related theories that inform our research design and, more specifically, dynamic preference heterogeneity by consumer segments (such as generations and cities).

2.1. Existing Literature on Consumer Preferences for EVs

Given the potential of EVs to address the global challenge regarding climate change oil dependency, researchers have been examining consumers' adoption behaviour and preferences for EVs, with driving factors generally falling into three categories: individual characteristics, product and service attributes, and EV-related policies (Liao et al., 2017; Singh et al., 2020).

Among the individual characteristics of EV buyers, the existing literature has focused on the influence of demographic characteristics (such as age, gender, education, income and household size; e.g., Hackbarth and Madlener, 2013, 2016; Huang et al., 2021a; Potoglou and Kanaroglou, 2007; Qian et al., 2019; Singh et al., 2020) and psychological factors (such as attitude, emotion, environmental awareness, symbolic view, social influence and personal values; e.g., Carley et al., 2013; Heffner et al., 2007; Huang and Qian, 2021b; Kim et al., 2014; Moons and De Pelsmacker, 2012; Qian and Yin, 2017; Rezvani et al., 2015). The product and service attributes affecting consumers' choice of EVs mainly include vehicle price, running or fuel cost, vehicle range, emission level, charging availability and speed (Helveston et al., 2015; Liao et al., 2017; Tanaka et al., 2014). For example, Qian et al. (2019) consider three types of charging infrastructure (i.e., public fast charging, public slow charging and home charging) as well as two levels of charging speed when examining consumers' stated choice preferences for EVs in China. Regarding policies, many studies have examined the influence of monetary incentives (such as purchase subsidy and tax rebate) and EV-friendly policies (such as free parking, bus lane access and less restrictions on vehicle licensing; e.g., Hackbarth and Madlener, 2013, 2016; Huang and Qian, 2018; Qian et al., 2019; Qian and Soopramanien, 2011).

In summary, considering the main objectives of our paper, previous research tends to employ cross-sectional data, overlooking how the influence of these aforementioned factors change over time, implying the following two limitations in terms of the insights that such studies can yield. First, while the existing body of work helps to understand consumer preferences for EV attributes at the specific time, these findings cannot be easily translated into a micro dynamic understanding of the future state of the EV market. In other words, the current literature cannot reveal the dynamic nature of consumer preferences in a changing market environment, where the latter is influenced by factors such as technological progress (e.g., better range of batteries) and policy changes (e.g., subsidies or wider coverage of battery charging stations). This is particularly critical in the market expansion stage of EVs due to the high level of policy uncertainty and frequent infrastructural changes (Silvia and Krause, 2016). Second, although extant studies have identified different segments (e.g., car owners and non-owners) as well as within-segment preference heterogeneity in EV markets (Yang et al., 2019; Qian and Soopramanien, 2015), it remains unclear as to how consumer preferences evolve when looking at the differences between different segments over time. Given the dynamic change of market composition over time, we argue that more empirical evidence is therefore needed to capture what may be called the longitudinal dynamics of preference heterogeneity for EVs across different segments (Huang et al., 2021a).

Carley et al. (2019) and Fan et al. (2020) represent two exceptions in the recent literature, as they attempt to empirically explore changes in consumer adoption intentions for EVs by collecting survey data at two points in time. Carley et al. (2019) collected data on American consumers' intention to purchase or lease EVs in 2011 and 2017, while Fan et al. (2020) collected data on Chinese consumers' acceptance of EVs in 2012 and 2017. However, the nature of their research design limits the insights into the nature of dynamic consumer preferences, in two regards. First, both studies collected survey data only twice; as such, they cannot study the possibility of any non-linear pattern in consumer preferences – which are likely to occur during the diffusion process of new technologies (Windrum et al., 2009). Second, neither conducted a longitudinal study with repeated data collection from the same group of respondents; rather, they collected survey data from different samples across two different years. As a result, the identified preference differences might be attributed to sample differences rather than a change in preferences of the same group of consumers across time.

2.2. Theories Related to Consumer Preferences for EVs

From a theoretical perspective, most studies in the literature have adopted behavioural theories to explain consumers' adoption intention for EVs, such as the theory of planned behaviour, the theory of reasoned action, the technology acceptance model and the value–attitude–behaviour framework (Qian and Yin, 2017; Rezvani et al., 2015; Singh et al., 2020). These papers broadly account for perceptions, attitudes and risks of adopting EVs at one specific time. However, they do not consider, for instance, attitude and behavioural change over time – unlike our research, which accounts for changes from a dynamic perspective on preferences in terms of various factors that may affect the adoption decision.

Our study is related to the diffusion of innovation theory (Rogers, 2003), which has been used to study EV adoption from the perspective of market evolution concerning a new product, whereby we consider, initially, two broad groups of consumers: those who have already adopted and those who have yet to adopt (Singh et al., 2020). However, this theory cannot fully explain whether the preference difference observed during the EV diffusion process is due to preference changes over time from the same consumers (i.e., within-subject difference) or different preferences for innovative technologies among different group of consumers (i.e., between-subject difference).

On the one hand, the diffusion of innovation theory argues that the EV diffusion process is jointly influenced by five factors: relative advantage, compatibility, complexity, trialability and observability of the innovation. Specifically, after innovations enter and gradually penetrate the market, consumer preferences are likely to evolve along with progress in vehicle or battery technologies (i.e., ‘relative advantage’), development of charging infrastructure (i.e., ‘compatibility’), personal use experience (i.e., ‘trialability’), reduced complexity of usage, and word of mouth or social influence from existing users (i.e., ‘observability’) (Rogers, 2003; Liao et al., 2017). On the other hand, the time perspective in Roger’s model proposes further segmenting consumer groups depending on when they adopt the innovation and the factors that differentiate them. The diffusion of innovation theory therefore classifies adopters of EVs into five segments: innovators, early adopters, early majority, late majority and laggards (Rogers, 2003). The existing literature on EV diffusion particularly is concerned with the identification of early adopters (Carley et al., 2013; Plötz et al., 2014) and how they influence attitudes and the likelihood of adoption by other groups (Axsen and Kurani, 2011; Kanger et al., 2019; Yu et al., 2016). Different preferences for EVs across these segments, and differences in their timing of adoption, are found to be associated with different levels of consumer characteristics, such as innovativeness (Schuitema et al., 2013). Therefore, our study complements the application of the diffusion of innovation theory in the domain of EVs because we capture consumer preference changes over time by examining dynamic preferences for EVs from the same group of consumers over multiple years. We also use this theory as the basis for studying preferences for different EV attributes by segment.

2.3. Dynamic Preferences for EVs by Generation and Geography

The existing literature on sustainable transition has underlined the importance of geographic and demographic characteristics (Hansen and Coenen, 2015). In the context of EVs, the existing literature has highlighted the heterogeneity in consumer attitudes towards EVs across different market segments, both demographically (e.g., Kim et al., 2014; Yang et al., 2019) and geographically (e.g., Huang and Qian, 2018; Huang et al., 2021a). However, little work has been done to show if preferences across these segments change over time; if they do, whether these changes occur homogeneously across segments; and what insights we can gain from studying such changes over time by comparing segment preferences.

2.3.1. Arising Preferences for EVs in Generation X

Generations X and Y are two generational groups typically studied by social scientists (e.g., Gurtner and Soyez, 2016). The former consists of those born in the 1960s and the 1970s, while the latter are those born from the early 1980s until the late 1990s, and such typology has been employed in consumer research in the Chinese context (e.g., O'Cass and Choy, 2008).

It is widely acknowledged that Generation Y is more receptive to digital technologies and social media because of living in the 'Information Age' (Hidrue et al., 2011). However, prior literature has largely overlooked this generational factor and particularly how the inter-generational heterogeneity for EVs has evolved over time. In contrast to the typical findings suggesting that EV buyers are younger than ICEV buyers (Pendergast, 2010), the penetration of EVs in China started from the more mature generation (i.e., Generation X), in line with the higher price of EVs. For example, in October 2017, only 23.8% of EV buyers in China were younger than 30 years old – much lower than the corresponding proportion among total car buyers of 43.2% (DaaS-Auto Research Center, 2018). Furthermore, the ongoing marketisation of EVs in China is making EVs less costly, and more affordable models are becoming available to various consumer segments, including Generation Y, who may have limited purchasing capacity. Additionally, on-demand EV-sharing is gaining momentum in the Chinese market, with the younger generations being the major users (Analysys, 2018). Thus, Generation Y may gain more personal EV experience over time, which would help to build a positive attitude towards EVs (Schmalfuß et al., 2017).

2.3.2. Geographical Preference Differences in EVs

The sustainable transition literature highlights the importance of geographical segmentation and the related characteristics (Hansen and Coenen, 2015; Huang et al., 2021a). In the U.S., the machine-learning based analysis of Bas et al. (2021) demonstrates that the county in which the respondents live is the most important factor associated with the propensity to adopt an EV. Cities of different sizes usually comprise consumers with distinct characteristics. In the context of China, the tier of a city, based on the urban population size, has been recognised as an important segmentation dimension when studying adoption of EVs (e.g., Huang and Qian, 2018; Lin and Wu, 2018; Qian et al., 2019). Cities of different sizes in China have different socioeconomic features, EV-related infrastructure, and local policies for EVs (Huang and Qian, 2018), so that cities in different tiers are at different stages of the EV diffusion process. Specifically, first- and second-tier cities are the first movers in the transition towards EVs, and Chinese consumers living in bigger cities have been buying more EVs than those in smaller cities (Ways, 2018).

However, recent significant market development has made EVs more accessible and affordable for consumers in smaller cities. This is indicated by the new growth pattern in China, where smaller cities have demonstrated a higher growth rate in EV adoption (DaaS-Auto Research Center, 2018). Based on their early study in 2016, Huang and Qian (2018) suggest that consumers in third-tier cities were less inclined to adopt EVs than those in bigger cities; more recently, Huang et al (2021a) find that consumers in smaller cities have been developing more positive preferences, along with the deeper market penetration of EVs. Thus, as the market evolves, there is a need to understand the dynamic nature of consumer preference heterogeneity so that, rather than adopting uniform policies, targeted strategic and policy initiatives are employed and adapted over time for different types of cities. This is important because uniform policies may not be suitable for the particular market context of China, where cities of different sizes occupy different stages of the diffusion curve as per Rogers's (2003) framework.

3. Method and Data

To demonstrate the real-time investigation of this socio-technical innovation transition, we conducted three waves of empirical study in the Chinese EV market. Specifically, we conducted three waves of SP experiment from same group of respondents across China, in 2017, 2018 and 2019, based on the same design. SP experiment, also known as choice-based conjoint analysis, has been widely used social science and transportation research to examine consumer choice across different alternatives (Rao, 2004; Louviere et al., 2020). Drawing on the three-wave SP experiment data, we used the discrete choice model to analyse consumer preferences, and in particular longitudinal differences, by accounting for systematic taste variations across different waves (Ortúzar and Willumsen, 2011). We also conducted an analysis on the dynamic preference heterogeneity for EVs across different city tiers and different generations over the three waves.

We collected and analysed three waves of data from 2017 to 2019 in light of both policy and market growth considerations. From the policy perspective, the central government in China decided in 2015 to extend the period for the EV purchase subsidy to 2020 (Helveston et al., 2015), and set a target of establishing one charging station for every 2,000 EVs by 2020 (Hall et al., 2017). Our three-wave data ended in 2020 and therefore is highly relevant given these policies; in particular, our examination of the dynamic effect of policies, including those relating to charging stations. From a market growth point of view, the two policies mentioned above fast-tracked the development of the Chinese EV market, rendering China the world's largest EV market by 2017 (Huang and Qian, 2018). By the end of 2019, the market share (in terms of sales) of EVs in the Chinese car market had reached 4.95% (China Passenger Car Association, 2020). Such market growth and penetration make it possible, and meaningful, to examine consumer preferences for EVs in China.

3.1. Design of the Stated Preference Experiment

In a typical SP experiment, researchers present hypothetical choice scenarios that mimic the actual choice situation that a consumer may face in the real market and invite respondents to make their choice. In this study, we included three choice alternatives in the SP experiment: an ICEV, a plug-in hybrid electric vehicle (PHEV) and a battery electric vehicle (BEV), where PHEVs can be driven by either gasoline or electricity, and BEVs are fully powered by electricity. The profiles of these three alternatives are specified using a range of product, service and policy attributes, largely based on the existing literature and the market practice (Liao et al., 2017; Wang et al. 2018). Table 1 outlines the attributes and their varying levels in the SP experiment.

Table 1: Attributes and levels of variation in SP experiment

Attributes	**Values and levels for variations**
Product attributes	
ICEV purchase price (10,000 CNY)	Specified by the respondents[1]
PHEV purchase price (10,000 CNY)	20% / 40% / 60% higher than similar-sized ICEV
BEV purchase price (10,000 CNY)	30% / 50% / 70% higher than similar-sized ICEV
ICEV annual running cost (10,000 CNY)	Market average based on vehicle price level[2]
PHEV annual running cost (10,000 CNY)	40% / 50% / 60% of that of similar-sized ICEV
BEV annual running cost (10,000 CNY)	10% / 25% / 40% of that of similar-sized ICEV
Driving range limit for ICEV (after full refuelling)	600 km (petrol)
Driving range limit for PHEV (after full refuelling and charging)	50 / 70/ 100 km (electricity) + 600 km (petrol)
Driving range limit for BEV (after full charging)	80 /150 / 200 km (electricity)
Service attributes	
Density of public fast service stations for ICEV	100% of existing petrol stations
Density of public fast service stations for PHEV and BEV	10% / 40% / 70% of existing petrol stations
Service speed for ICEV in public fast service stations	5 mins (petrol refuelling)
Service speed for PHEV in public fast service stations	10 / 20 / 30 mins (fast charging)
Service speed for BEV in public fast service stations	5 mins / 15 mins / 30 mins (fast charging)
Density of public slow charging posts for PHEV and BEV	10% / 40% / 70% of available parking spaces
Permission to install home slow charging post for PHEV and BEV	Yes / No
Charging time in slow charging post for PHEV	4 / 6 / 8 hours
Charging time in slow charging post for BEV	6 / 8 / 10 hours
Policy attributes	
Government subsidy (10,000 CNY) for ICEV	0% (no subsidy)
Government subsidy (10,000 CNY) for PHEV	0% / 10% / 20% of purchase price
Government subsidy (10,000 CNY) for BEV	10% / 20% / 30% of purchase price
Vehicle licensing policy for ICEV	Lottery-based licensing
Vehicle licensing policy for PHEV	Prioritised licensing / Lottery-based licensing
Vehicle licensing policy for BEV	Prioritised licensing / Lottery-based licensing

[1] Respondents previously selected a preferred price for an ICEV that represents their preferred vehicle class: 80,000 for basic class, 150,000 for middle class, 250,000 for upper-middle class and 400,000 for luxury class.

[2] Market average level: 25,000 CNY for basic class, 40,000 CNY for middle class, 48,000 CNY for upper-middle class and 50,000 CNY for luxury class.

Specifically, we included three product attributes (vehicle purchase price, annual running cost and driving range) in the SP experiment, following the prior literature on EV choice (Hoen and Koetse, 2014; Qian and Soopramanien, 2011; Eggers and Eggers, 2011). Vehicle purchase price is the one-time upfront cost to acquire the vehicle ownership. The purchase price of ICEVs is adapted from the intended vehicle price range that each respondent chose in the survey prior to the start of the SP experiment. We then applied the pivoting design technique (Hensher et al., 2015) to create a more realistic choice situation for each respondent[3]. In our SP experiment, the purchase prices of the two types of EV (i.e., PHEV and BEV) were hypothesised to be higher than those of similar-sized ICEVs. Specifically, with reference to the price of an ICEV, the price of PHEVs can be 20%, 40% or 60% higher, and the price of a BEV can be 30%, 50% or 70% higher. Annual running cost consists of the fuel cost and maintenance expense. We first determined the market average running cost for each vehicle class corresponding to the respondent's intended price levels. The running cost for ICEVs was then used as the reference for the same attribute for both PHEVs and BEVs. We assumed that both types of EVs have proportionally lower running cost than ICEVs, each with three varying levels. Driving range, defined as the maximum distance that a vehicle can drive after full refuelling or recharging, is another important attribute affecting EV choice (Franke and Krems, 2013). For ICEVs, we assumed a fixed driving range of 600 kilometres. The driving range of PHEVs is a combination of the fixed petrol-powered range of ICEVs (i.e., 600 km) and the varying electricity-powered

[3] With regard to the intended vehicle price, there are four levels: 80,000 CNY for basic class, 150,000 CNY for middle class, 250,000 CNY for upper-middle class, and 400,000 CNY for luxury class; the corresponding annual running cost is 25,000 CNY for basic class, 40,000 CNY for middle class, 48,000 CNY for upper-middle class, and 50,000 CNY for luxury class.

range of between 50 and 100 kilometres. For BEVs, the driving range limits were assumed to vary among 80, 150 and 200 kilometres.

Following Qian et al. (2019), this study distinguishes different types of service attributes, including (public) fast refuelling or recharging for ICEVs and EVs, and (home or public) slow charging for EVs. As the perceived utility of the refuelling and recharging service can be influenced by both service availability and service speed, we specified the following five service attributes in our SP experiment: density of fast service stations, density of slow service posts, service speed to complete the fast service, service speed to complete the slow service and home charging capability. As fast charging stations for EVs are not as established as petrol service stations for ICEVs (Tanaka et al., 2014), the density of fast service stations for EVs was assumed to be a varying proportion (i.e., 10%, 40%, 70%) of that of the existing petrol stations (Achtnicht et al., 2012). Similarly, the density of slow charging posts was assumed to be available in 10%, 40% or 70% of public parking spaces (Qian and Soopramanien, 2011). Fast and slow charging services differ significantly in their service speed (Junquera et al., 2016). As suggested by current charging technologies, EVs usually take no longer than 30 minutes to fully charge the battery in fast charging stations, but may take up to 10 hours if using the slow charging option. Additionally, we introduce a dummy attribute of ‘home charging capability’, which is specific in China where it is sometimes difficult or even prohibited for consumers to install a privately accessed charging post at their residence (Wang, 2015; Yang, 2016).

Our SP also includes two policy attributes – purchase subsidy and vehicle licensing policy –

two major government policy interventions to encourage EV adoption in China (Wang et al., 2018). Purchase subsidy is a widely used policy to incentivise EV adoption (Helveston et al., 2015; Zhang and Qin, 2018). We define this attribute as a varying proportion of the purchase price of an EV; generally, the subsidy for a BEV would be higher than that for a PHEV, given that BEVs consume no oil and are hence more encouraged for the transition to low carbon (Xing et al., 2016). In addition, several big cities in China (e.g., Beijing, Shanghai, Shenzhen and Guangzhou) regulate licensing for ICEVs (e.g., via the lottery process in Beijing and auction mechanism in Shanghai), to control the rapid growth of vehicle ownership (Li, 2018; Yang et al., 2017), but EVs are usually exempt from such regulation or have a higher chance of being licensed. Therefore, in our SP experiment, we assumed that ICEVs face a lottery-based licensing policy, while PHEVs and BEVs might be licensed either immediately without any additional cost or by following the same lottery process.

With the attributes and levels described above, a full-factorial design of the SP experiment would lead to over 38 million possible configured scenarios (= $3^{14} * 2^{3}$), which is unfeasible to implement in terms of data collection. Therefore, we implemented a D-efficient design by using SAS 9.4, which minimises the D-error of the asymptotic variance-covariance matrix for the experiment design (Rose and Bliemer, 2009). Specifically, we adopted the D-efficient design in Qian et al. (2019), which consists of 24 choice scenarios.[4] In each wave of data collection,

[4] The minimal number of scenarios/situations should be equal to or greater than the number of (design-related) parameters, not including constants, plus one (Kuhfeld, 2005; Rose and Bliemer, 2009). Since one parameter is incurred for each two-level attribute and one parameter is incurred for each three-level continuous attribute, there are 17 parameters given 17 attributes, and thus the minimal number of scenarios/situations required is 18 (= 17 + 1).

each respondent was randomly assigned four choice scenarios from the total of 24; see Figure 1 for a sample choice scenario.

3.2. Data Collection Procedure

The following describes the main steps of the data collection in this study:

(1) We began the recruitment of participants in early 2016 by employing 46 university students as survey assistants; their home cities are located in the 24 automobile market clusters across China identified by McKinsey (Wang et al., 2012).

(2) Prior to the recruitment of participants, we provided our survey assistants with systematic training on the purpose of the project, basic EV knowledge and communication skills on how to recruit participants. By adopting a quota sampling approach with a sample size of 1,300, the number of participants in each automobile cluster is proportional to their car market share in 2020 as predicted by McKinsey (Wang et al., 2012).

(3) Our survey assistants contacted households in their hometown cities and invited those who were willing to participate in the study for three years to join in. This recruitment process was completed in June 2016 when the participant quota was met in every cluster. As a result, we successfully recruited a total of 1,282 valid participants who agreed to participate into our longitudinal study. Each member was assigned a unique identification number to track their responses over the following three years.

Figure 1: Sample choice scenario.

	Attributes	**Petrol Vehicle**	**Plug-in Hybrid Electric Vehicle (PHEV)**	**Battery Electric Vehicle (BEV)**
Product attributes	Purchase price	80,000 CNY	96,000 CNY	104,000 CNY
	Running cost	20,000 CNY per year	12,000 CNY per year	5,000 CNY per year
	Driving range limit	600 km (petrol)	50 km (electricity) + 600 km (petrol)	200 km (electricity)
Service attributes	Density of public fast service stations	100% (all existing petrol stations)	Equivalent to 70% of existing petrol stations	Equivalent to 70% of existing petrol stations
	Service time in public fast service station	5 mins (petrol refuelling)	10 mins (fast charging)	30 mins (fast charging)
	Density of public slow charging posts	N/A	70% of available parking spaces	70% of available parking spaces
	Permission to install home slow charging post	N/A	Not permitted	Not permitted
	Charging time in slow charging post	N/A	4 hours (slow charging)	8 hours (slow charging)
Policy attributes	Government subsidy	No subsidy	No subsidy	31,200 CNY (30% of purchase price)
	Vehicle licensing policy	Lottery-based licensing	Prioritised licensing	Lottery-based licensing

Imagine that you need a new car, which car described above would you most prefer?

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

(4) We established the SP experiment and other questions in an online questionnaire hosted by an Internet-based survey platform. We then conducted a pilot survey among 10 volunteers to test the accessibility and readability of the survey design, which led to improvements in terms of lexicon, wording and visual aids.

(5) We started the first-wave research in January 2017, when our survey assistants returned to their home cities for the winter holidays and invited the subscribed participants to access our online questionnaire. By March 2017, the first wave had collected 1,072 valid responses. In the second and third waves, we followed the same process to collect 1,025 and 849 valid responses in early 2018 and early 2019 respectively[5].

(6) After consolidating all three waves of the data and checking the participants' consistency (e.g., household identity, generation and gender) across the three waves, we identified 507 participants who had participated all three waves of research and thus were included in the final sample for data analysis.

It is worth noting that our quota-based sampling strategy improved the sample representativeness for empirical studies in the context of China. This is because our sample has a wide geographical coverage of consumers across the 24 automobile clusters in China, while most existing studies on EV adoption in China are based on data collected either from one or a few mega cities (e.g., Helveston et al., 2015; Wang et al., 2008) or using convenience sampling (e.g., Qian and Soopramanien, 2011). Importantly, our sampling approach, as well as the

[5] In our SP experiment, there were 24 choice situations unchanged across three years, but given the nature of SP experiment, in each wave of data collection, we randomly allocated four scenarios to each respondent. Thus, in the second and third waves, respondents may not see the exactly same choice scenarios as in the previous wave(s).

sampling frame, has been applied and validated in recent empirical studies (e.g., Huang et al., 2021a, 2021b; Huang and Qian, 2021a, 2021b). The next section presents further analysis of the sample characteristics.

3.3. Model Specification

We used a discrete choice model based on the theory of random utility maximisation (Train, 2009). In any choice scenario of our SP experiment, individual *i* in choice scenario *m* (*m* = 1 to 4) of wave *t* (t = 1 to 3) facing alternative *n* attains utility U_{inmt}, consisting of an observable part V_{inmt} and an error component ε_{inmt}.

$$U_{intm} = V_{intm} + \varepsilon_{intm}. \tag{1}$$

Underpinned by the utility maximisation assumption, an individual is most likely to choose the alternative that provides the greatest utility. Among the range of specifications for discrete choice models, the multinomial logit (MNL) model is often used due to its simplicity. The MNL model assumes V_{intm} is deterministic and the error component ε_{intm} follows the type I Extreme Value distribution. However, the MNL model holds the property of Independent from Irrelevant Alternatives (IIA), where consumers perceive all alternatives in a choice set to be independent from each other (Train, 2009). Therefore, the MNL model is incapable of examining heterogeneous preferences for EVs (Qian and Soopramanien, 2011, 2015). To relax the IIA assumption and capture preference heterogeneity, many researchers adopt the mixed logit (MXL) model, which allows for random taste variation among different individuals and thus unrestrictive substitution patterns between different alternatives (Train, 2009).

In this study, we used the error component logit (ECL) model,[6] one of the MXL model specifications employed by similar studies for data calibration (e.g., Qian et al., 2019; Cherchi, 2017). To examine consumers' dynamic preference heterogeneity for EVs, we specified the perceived utility of different types of cars n in choice situation m of wave t as a function incorporating car-related attributes (as listed in Table 1) and consumer demographics:

$$U_{intm} = \alpha_n + \alpha_{nt} + (\beta + \beta_t)X_{intm} + \gamma_n y_{it} + w_{in} + \varepsilon_{intm} \tag{2}$$

where α_n is an alternative-specific constant (ASC) that captures the average utility of each type of car, which is invariant across different waves, while α_{nt} is the systematic taste variation of ASC in specific wave t. The choice attribute X_{intm} may change for different consumers, alternatives, choice situations and/or wave. β is the vector of the coefficients for the observed attributes in the baseline wave (i.e., Wave 1 in this empirical setting), and β_t is the wave-specific variation in addition to the coefficient in the baseline wave. y_{it} is the individual characteristics that may change over time t, and γ_n is a coefficient vector interacting with ASC of PHEV and BEV respectively, using ICEV as the reference. To capture the unobserved heterogeneity, w_{in} is the alternative-specific error component, which is assumed to follow the normal distribution with zero mean, for which the standard deviation will be estimated (Hensher et al., 2015).

[6] We used Nlogit 5.0 software in our estimation, and configured the maximum likelihood estimation process for the ECL model using the standard Halton sequence suggested by Louviere et al. (2010) and employing 200 Halton random draws.

Table 2: Demographic characteristics of the unweighted sample

Sample Characteristics	Category	Wave 1 (2017)	Wave 2 (2018)	Wave 3 (2019)	Longitudinal Difference[1]
Sample size			507		/
Generation	Generation X (born before 1977)		35.70%		
	Generation Y (born in 1977 or later)		64.30%		/
Gender	Male		34.32%		
	Female		65.68%		/
Highest education level	Below senior high school	2.96%	3.16%	3.35%	
	Senior high school	15.78%	12.03%	9.86%	
	Junior college	12.43%	12.82%	12.03%	χ^2= 12.406, *df*=8, *p*=0.134
	Bachelor	63.31%	65.29%	65.68%	
	Postgraduate	5.52%	6.71%	9.07%	
No. of private cars in household	0	11.44%	11.44%	9.27%	
	1	58.58%	55.62%	55.62%	χ^2= 11.999, *df*=6, *p*=0.062
	2	27.02%	26.82%	27.61%	
	More than 2	2.96%	6.11%	7.50%	
Family size (number of people)	1	4.54%	5.72%	6.90%	
	2	15.19%	15.38%	22.88%	
	3	53.06%	50.69%	43.39%	χ^2= 19.714, *df*=10, *p*=0.032
	4	16.37%	17.55%	15.78%	
	5	6.90%	6.51%	6.31%	
	6 or more	3.94%	4.14%	4.73%	
No. of young children (aged below 18) in the household	0	70.81%	70.41%	70.02%	
	1	18.34%	20.91%	21.50%	χ^2= 8.713, *df*=6, *p*=0.190
	2	9.27%	5.72%	6.51%	
	3 or more	1.58%	2.96%	1.97%	
Car driving experience (year)	No experience	41.62%	33.33%	24.46%	
	Less than 1	20.12%	22.29%	24.06%	
	1–3	9.86%	15.19%	19.33%	χ^2= 41.471, *df*=10, *p*<0.001
	4–6	7.10%	7.10%	7.50%	
	7–9	7.10%	7.10%	8.68%	
	10 or longer	14.20%	14.99%	15.98%	
Tier of city[2]	1st tier (big city)	15.98%	15.78%	17.75%	
	2nd tier (big city)	14.99%	17.55%	14.60%	
	3rd tier (midsized city)	58.97%	55.42%	57.59%	χ^2= 4.436, *df*=8, *p*=0.816
	4th tier (small city)	5.52%	6.90%	6.51%	
	5th tier (small city)	4.54%	4.34%	3.55%	

[1] Examination of longitudinal difference is based on Chi-square test.

[2] The classification of city tiers in China follows the recent national standard from the State Council of China (http://www.gov.cn/zhengce/content/2014-11/20/content_9225.htm). Urban population data in 2017 retrieved from Ministry of Housing and Urban-rural Development of China (http://www.mohurd.gov.cn/xytj/tjzljsxytjgb/jstjnj/index.html) was used.

4. Analysis

4.1. Sample Description

Table 2 summarises the demographic information of our participants across three waves. Specifically, we have slightly more participants from Generation Y than Generation X, and more female members than male. Such composition remained robust across the three waves of data collection. Similar to many empirical studies in the context of China (e.g., Qian and Yin, 2017), more than 60% of participants held a bachelor or higher degree. The distributions of educational level and number of children in the household (aged below 18) among our participants remained fairly stable over these years (i.e., 2017 to 2019), as indicated by Chi-square tests. In terms of household car ownership level, approximately 90% of the participants live in households owning private car(s). There was slow growth in private car ownership over the three years ($\chi^2 = 11.999$, $df = 6$, $p = 0.062$), but significant growth in car driving experience ($\chi^2 = 41.471$, $df = 10$, $p < 0.001$).

Regarding family size, three-member households accounted for the highest proportion over the three years, but the proportion of smaller households increased year by year, with statistical significance shown by the Chi-square test on family size change over these three years ($\chi^2 = 19.714$, $df = 10$, $p = 0.032$). Our sample also has a wide distribution in terms of the tier of city that participants came from: about 16% and 15% of our sample came from first-tier and second-tier cities respectively (i.e., big cities), around 57% from third-tier cities (i.e., midsized cities) and the remaining 10% from lower-tier cities (i.e., small cities). The distribution of city tiers remained stable over the three years of our study ($\chi^2 = 4.436$, $df = 8$, $p = 0.816$).

4.2. Results of Discrete Choice Modelling[7]

We first estimate a baseline MXL model (i.e., Model 1) with car-related attributes in our SP experiment and participants demographics by pooling data from all waves together, where each respondent offers a total of 12 observations across the three waves (i.e., four choice tasks in each wave). Then, Model 2 examines the potential changes in consumer preferences for EVs and the key attributes over time, by accounting for the systematic taste variation recommended by Ortúzar and Willumsen (2011). We extend this analysis by accounting for the changes in EV preferences across different generations (i.e., Model 3) and different sized cities (i.e., Model 4) respectively. The analysis results for the main models and extended analysis are presented in Table 3 and Table 5 respectively.

4.2.1. Dynamic Consumer Preferences for EVs and the Key Attributes

The baseline model (i.e., Model 1) pools the three waves of SP data, without distinguishing the differences across the three waves. Overall, the estimates for product, service and policy attributes show that our participants prefer EVs with lower purchase price, lower running cost and longer driving range. They also find higher density of fast (slow) charging stations, shorter time of fast (slow) charging and capability for home charging attractive, with purchase subsidy and prioritised licensing also perceived important.

[7] Because we oversampled participants in midsized cities, we reweighted the sample in the discrete choice modelling according to the actual proportion of urban population in each city tier in China, following Ministry of Housing and Urban-rural Development of China, which provides urban population data for each prefecture city (www.mohurd.gov.cn/xytj/tjzljsxytjgb/jstjnj/w02019012421874448287322500.xls).

Table 3: Estimation results of main models

Variables	Model 1 (Baseline model)		Model 2	
	coefficient	**t-ratio**	**coefficient**	**t-ratio**
Alternative specific constants (ASCs)[1]				
For PHEV	0.886	1.270	0.328	0.440
For BEV	1.356 *	1.500	0.658	0.660
Standard deviation of error component				
For ICEV	2.957 ***	21.240	2.975 ***	21.150
For PHEV	1.263 ***	7.800	1.243 ***	7.540
For BEV	1.817 ***	13.690	1.829 ***	13.740
Product, service and policy attributes				
Vehicle purchase price (10K CNY)	-0.051 ***	-7.690	-0.051 ***	-7.660
Annual running cost (10K CNY)	-0.368 ***	-4.780	-0.500 ***	-4.370
Driving range limit after full charging or refuelling	0.002 ***	2.690	0.002 ***	2.690
Density of public fast service stations (%)	0.006 ***	3.420	0.003	1.090
Service time in fast service station (mins)	-0.022 ***	-6.850	-0.022 ***	-6.760
Density of slow charging posts (%)	0.005 ***	3.000	0.005 ***	2.960
Permission to install home slow charging post	0.388 ***	4.520	0.272 ***	2.270
Charging time in slow charging posts (hours)	-0.053 ***	-3.090	-0.052 ***	-3.050
Government subsidy for purchase (10K CNY)	0.056 ***	5.710	0.055 ***	5.610
Prioritised vehicle licensing [2]	0.458 ***	8.540	0.451 ***	5.800
Changes in consumer preferences for EVs and key attributes across waves[3]				
ASC for PHEV * Wave 2			**1.414 *****	**2.790**
ASC for PHEV * Wave 3			0.452	0.930
ASC for BEV * Wave 2			**1.484 ****	**2.340**
ASC for BEV * Wave 3			0.749	1.240
Annual running cost * Wave 2			**0.239 ***	**1.400**
Annual running cost * Wave 3			**0.226 ***	**1.440**
Density of fast service station * Wave 2			**0.013 *****	**2.850**
Density of fast service station * Wave 3			0.001	0.160
Permission to install home slow charging post * Wave 2			0.207	0.980
Permission to install home slow charging post * Wave 3			0.231	1.200
Prioritised vehicle licensing * Wave 2			0.115	0.900
Prioritised vehicle licensing * Wave 3			-0.076	-0.630
Demographic characteristics for each type of EVs				
Male * PHEVs	-0.393 **	-1.820	-0.414 **	-1.900
Male * BEVs	-0.557 **	-2.320	-0.571 ***	-2.360
Highest education level * PHEVs	0.093	0.790	0.100	0.840
Highest education level * BEVs	0.071	0.540	0.083	0.620
No. of cars in the household * PHEVs	0.220 *	1.500	0.214 *	1.460
No. of cars in the household * BEVs	0.092	0.550	0.085	0.510
Family size * PHEVs	0.064	0.690	0.069	0.750
Family size * BEVs	0.107	1.030	0.116	1.100
Car driving experience in year * PHEVs	-0.125 **	-1.760	-0.130 *	-1.820
Car driving experience in year * BEVs	-0.157 **	-2.020	-0.167 **	-2.120
Intended Price Range (100k-300k CNY) * PHEVs	-0.124	-0.290	-0.106	-0.250
Intended Price Range (100k-300k CNY) * BEVs	-0.997 **	-2.110	-0.964 **	-1.990
Intended Price Range (over 300k CNY) * PHEVs	-1.393 ***	-2.910	-1.349 ***	-2.780
Intended Price Range (over 300k CNY) * BEVs	-2.416 ***	-4.320	-2.354 ***	-4.120
Generation X [4] * PHEVs	0.391 *	1.380	0.405 *	1.420
Generation X * BEVs	0.596 **	1.990	0.624 **	2.060
Living in small city [5] * PHEV	-0.817 ***	-3.530	-0.831 ***	-3.560
Living in small city * BEV	-1.056 ***	-4.080	-1.054 ***	-4.010
Number of parameters	33		45	

Variables	Model 1 (Baseline model)	Model 2
Observations	7,098	7,098
Log-likelihood of MXL at convergence	-5607.55	-5597.40
Log-likelihood of MNL at convergence	-7101.16	-7088.73
McFadden Pseudo R-squared	0.263	0.265
Log-likelihood ratio test versus the Baseline Model 1		20.30 (*p*=0.062)

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$, all in one tail.
Sample is reweighted according to the actual proportion of urban population in each city tier, following Ministry of Housing and Urban-rural Development of China, which provides urban population data for each prefecture city (www.mohurd.gov.cn/xytj/tjzljsxytjgb/jstjnj/w02019012421874448287322500.xls). The actual ratio of urban population in each city tier is as follows: first-tier (12.37%); second-tier (8.83%); third-tier (48.25%); fourth-tier (23.53%); fifth-tier (7.01%).
[1] ICEV is the reference alternative for ASCs. [2] Lottery-based licensing as the base category. [3] Wave 1 as the reference year. [4] Generation Y as the base category. [5] Living in big and midsized cities as the base category.

In Model 2, we examine whether and how consumer preferences for EVs would change over time. This is achieved by interacting the wave dummy variables (where wave 1 is the reference year) with the ASCs of PHEV and BEV. We also interact these wave dummy variables with key attributes to capture the dynamic consumer preferences for these attributes over time.[8] Model performance is compared by the log-likelihood function at convergence. As shown in Table 3, Model 2 produces a converged log-likelihood value of −5597.40; better than Model 1, as indicated by the likelihood ratio test ($\chi^2 = 20.30$, $df = 12$, $p = 0.062$). This means that the inclusion of interaction terms with different waves improves the model performance. In the ECL specification of Model 2, we find that all error components yield a standard deviation significantly larger than zero ($p < 0.001$), with such significant variance implying a high level of preference heterogeneity across all three types of cars (Train, 2009).

[8] Variables involved in interaction with wave dummies consist of annual running cost, density of fast charging stations, permission to install home slow charging post, prioritized licensing policy, and two ASCs (for PHEV and BEV). Similar modelling approaches of capturing systematic taste variation have been employed by Grisolía et al. (2015), Huang and Qian (2018) and Qian et al. (2019).

Given its superior performance, we discuss the results of Model 2 for consumer preferences and the changes for EVs and key attributes as well as participants' demographics. While the baseline model indicates three-wave-average estimates, Model 2 further identifies dynamic preferences for several key attributes across the three waves. Specifically, for annual running cost, density of fast charging stations, home charging capability, prioritised licensing policy and two ASCs, estimates for Wave 1 are shown in the *Product, service and policy attributes* section of Table 3, while preference changes in Wave 2 and Wave 3 compared with Wave 1 are presented in the *Changes in consumer preferences for EVs and key attributes across waves* section of Table 3.

Using ICEVs as the reference group, we find the ASCs for both PHEVs and BEVs are statistically insignificant with positive signs. This suggests that when controlling car-related attributes for EVs and participants demographics, participants show indifferent preferences overall for both types of EVs in Wave 1. Regarding the preference changes for each type of EVs across different waves, we find that consumers have stronger preferences for both PHEVs and BEVs in Wave 2 than in Wave 1, as indicated by the significant interactions between the wave 2 dummy with the ASCs for PHEVs (β = 1.414, t = 2.79) and BEVs (β = 1.484, t = 2.34) respectively. Furthermore, we find the insignificant difference on consumer preferences for each type of EVs in Wave 3 compared to in Wave 1, which indicates consumers' declining preference from Wave 2 to Wave 3. Thus, we observe some non-linearity effects in consumer preferences for EVs across three years thus supporting one of our contentions that our approach can reveal such effects compared to those studies that are either cross-sectional or based on two waves of survey data only.

Product attributes include purchase price, annual running cost and driving range limit, for which all estimated coefficients are statistically significant. The interaction terms for product attributes show that participants' sensitivity on running cost was lower in Wave 2 and Wave 3 than in Wave 1, as indicated by the positive coefficients of these interactions in Wave 2 (β = 0.239, t = 1.40) and Wave 3 (β = 0.226, t = 1.44).

Regarding the service attributes, the density of slow charging posts is significant at the 0.1% level in Wave 1. While the density of fast charging stations is insignificant in Wave 1, the estimated interaction shows that the coefficient of the interaction term between this attribute and Wave 2 dummy is positive and significant (β = 0.013, t = 2.85), but consumer preference for this attribute does not vary between Wave 1 and Wave 3 (β = 0.001, t =0.16). These findings suggest that participants were more likely to value the density of fast charging stations in Wave 2 than in both Wave 1 and Wave 3. In addition, as the most convenient slow charging approach, home charging capability is considered a significant service attribute affecting consumers' choice (β = 0.272, t = 2.270) in Wave 1. Model 2 further shows that participants were consistently valuing the importance of this service attribute across the three waves, as indicated by the positive but insignificant estimates from Wave 2 (β = 0.207, t = 0.98) and Wave 3 (β = 0.231, t = 1.20). Similarly, participants are also found to have consistently strong preferences for prioritised vehicle licensing policy for EVs, as indicated by the positive and significant effect in the baseline wave while the insignificant changes in following two waves.

We also control for a wide range of participants' demographics on their preferences for EVs by interacting a range of demographic variables and ASCs for PHEVs and BEVs, with reference to ICEVs. On a three-wave average, we notice that participants who are female, living in car-owning households and older than 40 are more likely to choose PHEVs, while females, those who have limited driving experience, and those older than 40 are more likely to adopt BEVs. To control for a potential endogeneity effect of the price range, we include the interaction of intended price ranges with ASCs in the baseline model, using the lowest intended price range (i.e., lower than 100,000 CNY) as the base category. Compared with ICEV adopters, both potential PHEV and BEV buyers are less likely to spend over 300,000 CNY on their car purchase, and, notably, the intended price range for BEV adopters is likely less than 100,000 CNY. This result suggests that EVs are generally favoured by participants with a limited budget. We do not find potential EV adopters significantly differ from ICEV adopters in terms of education level or household size on a three-wave average. For city of residence, we use participants living in big and midsized cities as the base category and find that, overall, consumers from small cities have negative preferences for EVs.

Table 4: Summary of WTP values for Key Attributes

Attributes	Estimated WTP in our study			WTP Estimates in the Literature (Converted to in CNY)
	Wave 1	Wave 2	Wave 3	
Annual running cost (CNY/CNY saving per year)				
Point estimate	9.76	5.10	5.35	Qian et al. (2019): 10 with 95% CI of [5; 24]; Khan et al. (2021): 4.367; Hackbarth and Madlener (2016): 7.4; Helveston et al. (2015): 32 (China) and 11.22 (US); Huang and Qian (2018): 2.53; Bansal et al. (2021): 0.87–5.79
95% CI	[4.96; 14.55]	[-0.20; 10.40]	[0.62; 10.07]	
Density of public fast service stations (CNY/ % increase)				
Point estimate	560	3,060	690	Huang and Qian (2018): 1,340; Hackbarth and Madlener (2016): 466–2,300; Tanaka et al. (2014): 349 (US), 235 (Japan)
95% CI	[-470; 1,600]	[1,430; 4,680]	[-560; 1,940]	
Having home charging capability (CNY)				
Point estimate	53,190	93,640	98,310	Qian et al. (2019): 91,039 with 95% CI of [35,518; 215,910]
95% CI	[7,430; 98,950]	[24,660; 162,610]	[35,860; 160,760]	Huang and Qian (2018): 17,110
Prioritized vehicle licensing (CNY)				
Point estimate	88,100	110,560	73,170	Qian et al. (2019): 106,144 with 95% CI of [60,658; 230,666];
95% CI	[51,590; 124,600]	[62,610; 158,510]	[33,000; 113,340]	Yang et al. (2017): 102,000 (Beijing), 85,000 (Shanghai)

4.2.2. *Willingness to Pay for Key Attributes*

Using the estimated coefficients of the key attributes and their changes across the three waves, as well as the estimated coefficient of vehicle purchase price, we calculate the willingness to pay (WTP) in vehicle purchase price for each key attribute in each wave as well as the 95% confidence intervals (CIs) by using the Delta method (Hensher et al., 2015).

Table 4 presents our estimated WTPs and their 95% CIs for key attributes in every wave. Specifically, our point estimate of the WTP for a 1 CNY saving in annual running cost was 9.76 CNY (with 95% CI of [4.96; 14.55]) in Wave 1, and then dropped to just over 5.0 CNY in the latter two waves (with 95% CI of [-0.20; 10.40] and [0.62; 10.07] respectively). This change in WTP for annual running cost can principally be attributed to the different income growth rates in the year before each wave of our data collection. According to the National Statistical Bureau of China, the growth rate of annual disposable income per capita was 6.5% in 2017, higher than that in 2016 (5.6%). The faster income growth in 2017 suggests the less sensitivity to the annual running cost, which thus helps explain the decreasing WTP for the saving in the annual running cost in wave 2 (i.e., in early 2018) compared with in the previous year. In addition, consumer income continuously increased in 2018, but the growth rate dropped to 5.6%, which corroborates the finding that there was no substantial decreasing in the WTP for the saving in annual running cost from wave 2 to wave 3. Overall, our estimate of the WTP in vehicle purchase price for the saving in annual running cost is largely aligned with the results in the prior literature. For example, Qian et al., (2019) find the Chinese consumers are willing to pay 10 CNY (with 95% CI of [5, 24]) in vehicle price for every CNY saving of annual running cost. Khan et al. (2021) show that Canadian consumers are willing to pay CAN$ 4,367 in vehicle purchase price to save CAN$ 1,000 per year in running cost. Hackbarth and Madlener (2016) report the average WTP of €1,056 for fuel cost reduction of €0.01 per km, equivalent to €7.4 per €1 saving on fuel cost considering the average mileage of 14,259 km for passenger cars in Germany[9]. Bansal et al. (2021) find that Indian consumers are willing to pay US$ 104 – 692 more in the purchase price to save US$ 1 per 100 km, which means their WTP for saving US$ 1 in annual running cost is between US$ 0.87 and 5.79 given the 230km average weekly mileage in India (Bansal et al., 2021). Helveston et al. (2015) find the Chinese consumers in 4 major cities (Beijing, Shanghai, Shenzhen and Chengdu) are willing to pay US$3,000 for US$0.01/mile decrease in operating costs. Considering the annual driving mileage of Chinese car owners around 15,000 km[10], their estimate of WTP in vehicle purchase price is about US$ 32 per $1 saving in the annual operating cost. In comparison, Huang and Qian (2018) report the estimated WTP per 1 CNY saving in annual running cost was only 2.53 CNY among the tier 2 and 3 cities.

Regarding the WTP in vehicle purchase price for a 1% increase in the density of public fast charging stations, its point estimate was only 560 CNY in Wave 1 (with 95% CI of [-470; 1,600]), which sharply increased to over 3,000 CNY in Wave 2 (with 95% CI of [1,430; 4,680]), and then dropped to 690 CNY in Wave 3 (with 95% CI of [-560; 1,940]). This non-linear pattern of WTP for the density of fast charging stations is in line with the changing ratio of new EVs to new fast charging posts in the corresponding years before each wave of data collection.

[9] https://topgear-autoguide.com/category/traffic/annual-mileage-in-germany-cars-cover-14259-km1607664895
[10] https://chejiahao.m.autohome.com.cn/info/2688469

According to the data extracted from China Electric Vehicle Charging Infrastructure Promotion Alliance[11], the ratio of the number of new EVs to the number of new fast charging posts increased from 18.7 in 2016 to 33.38 in 2017 and then dropped to 26.16 in 2018, which effectively made consumers in early 2018 (i.e., wave 2) to perceive the increased scarcity of fast-charging stations and thus value this infrastructure much higher in early 2017 (i.e., wave 1). Furthermore, the number of new fast charging posts in 2018 doubled from the number in 2017, so that the ratio dropped to 2.62 in spite of the continuous growth of EV sales in 2018, which led to the reduced WTP for the 1% improved density of fast charging stations in wave 3. Our estimate in this WTP value is broadly in line with the results from the prior literature. For example, Huang and Qian (2018) find that Chinese consumers are willing to pay 1,340 CNY in vehicle price for 1% increase in the density of EV charging stations. Hackbarth and Madlener (2016) report the WTP ranging between €60 (466 CNY) and €296 (2,300 CNY) for 1% increase in fuel availability. Also, Tanaka et al. (2014) find that the US and Japanese consumers have the WTP of US$ 49.8 (349 CNY) and US$ 33.6 (CNY 235) respectively for 1% increase in the availability of alternative fuel stations.

It is important to note that the WTP estimates for both home charging capability and prioritized vehicle licensing are consistently significant across the three waves. Such significant estimates actually mean that Chinese consumers have been consistently valuing the importance of home charging capability and whether they can get the vehicle licensing easily (without going through lottery process) in their choice decision for EVs during the three years of this study.

[11] http://www.evcipa.org.cn/ and its WeChat business account (中国充电联盟)

Specifically, our point estimate of the WTP for home charging capability was 53,190 CNY in Wave 1 with 95% CI of [7,430; 98,950], which then increased to over 90,000 CNY in the following two waves with 95% CI of [24,660; 162,610] and [35,860; 160,760] respectively. Our estimate is consistent with the WTP value reported in Qian et al. (2019), who find Chinese consumers are willing to pay 91,039 CNY on average for the home charging capability, with a wider 95% CI. In comparison, Huang and Qian (2018) find the smaller WTP of 17,110 CNY in second and third tiers of Chinese cities for the home charging capability. Furthermore, our point estimate of the WTP for prioritised licensing varies between 73,000 and 110,000 CNY over the three waves. Our result is largely aligned with the WTP value of 106,144 CNY that Qian et al. (2019) estimate for the prioritized license for EVs. Similarly, Yang et al. (2017) find consumers in Beijing and Shanghai are willing to give up the subsidy with the value of 102,000 and 85,000 CNY respectively to get their EV licensed immediately, rather than go through the lottery or auction process for getting the car plate for ICEVs. In summary, such changes in WTPs across multiple years further demonstrate the value of analysing the dynamics of consumer preferences for EVs over multiple time periods.

4.2.3. Dynamic Preferences for EVs in Different Generation and City Segments

We now examine how consumer preferences for EVs evolve over time between different generations or across different city tiers. When examining generational effects for EV preferences (see Model 3 in Table 5), we introduce the three-way interactions involving the ASC of each alternative (i.e., PHEV or BEV), the generation (i.e., Generational X or Y) and the longitudinal waves of data (i.e., Wave 2 or 3, using Wave 1 as the reference). Most estimated parameters in Model 3 remain robust, as in the baseline model (i.e. Model 1). The goodness-of-fit (i.e., log-likelihood value) does not significantly differ from that of the baseline model (χ^2 = 7.100, df = 6, p > 0.10), implying that adding a generational effect by different waves cannot strongly improve the explanatory power of the model. Most estimated coefficients of the three-way interactions involving generation, time wave and each type of EVs are not significantly different from zero, which indicates no significant change over these three years in each generation regarding their preferences for both PHEVs and BEVs.

Table 5: Estimation results of additional models

Variables	Model 3		Model 4	
	coefficient	t-ratio	coefficient	t-ratio
Alternative specific constants (ASCs) [1]				
For PHEV	0.914	1.260	1.143 *	1.600
For BEV	1.311 *	1.390	1.515 *	1.640
Standard deviation of error component				
For ICEV	2.956 ***	21.300	2.900 ***	20.960
For PHEV	1.196 ***	7.140	1.250 ***	7.580
For BEV	1.864 ***	14.090	1.828 ***	13.780
Product, service and policy attributes				
Vehicle purchase price (10K CNY)	-0.051 ***	-7.680	-0.052 ***	-7.750
Annual running cost (10K CNY)	-0.369 ***	-4.790	-0.368 ***	-4.790
Driving range limit after full charging or refuelling	0.002 ***	2.720	0.002 ***	2.680
Density of public fast service stations (%)	0.006 ***	3.400	0.006 ***	3.330
Service time in fast service station (mins)	-0.022 ***	-6.830	-0.022 ***	-6.780
Density of slow charging posts (%)	0.005 ***	3.000	0.005 ***	2.880
Permission to install home slow charging post	0.387 ***	4.500	0.391 ***	4.530
Charging time in slow charging posts (hours)	-0.053 ***	-3.080	-0.053 ***	-3.100
Government subsidy for purchase (10K CNY)	0.056 ***	5.690	0.056 ***	5.660
Prioritised vehicle licensing [2]	0.457 ***	8.530	0.459 ***	8.570
Demographic factors interacted with ASCs				
Male * PHEVs	-0.400 *	-1.860	-0.426 *	-1.960
Male * BEVs	-0.551 **	-2.290	-0.553 **	-2.300
Highest education level * PHEVs	0.095	0.810	0.092	0.780
Highest education level * BEVs	0.074	0.550	0.068	0.520
No. of cars in the household * PHEVs	0.235 *	1.610	0.243 **	1.660
No. of cars in the household * BEVs	0.104	0.620	0.114	0.680
Family size * PHEVs	0.048	0.520	0.053	0.580
Family size * BEVs	0.098	0.920	0.094	0.900
Car driving experience in year * PHEVs	-0.129 **	-1.800	-0.136 **	-1.930
Car driving experience in year * BEVs	-0.169 **	-2.140	-0.172 **	-2.210
Intended Price Range (100k-300k CNY) * PHEVs	-0.100	-0.240	-0.108	-0.260
Intended Price Range (100k-300k CNY) * BEVs	-0.974 **	-2.020	-0.960 **	-2.050
Intended Price Range (over 300k CNY) * PHEVs	-1.365 ***	-2.830	-1.346 ***	-2.850

Variables	Model 3		Model 4	
	coefficient	t-ratio	coefficient	t-ratio
Intended Price Range (over 300k CNY) * BEVs	-2.406 ***	-4.230	-2.357 ***	-4.280
Generation X [4] * PHEVs	-0.028	-0.070	0.414 *	1.480
Generation X * BEVs	0.441	1.000	0.628 **	2.090
Living in small city [5] * PHEV	-0.817 ***	-3.520	-2.156 ***	-5.470
Living in small city * BEV	-1.046 ***	-3.980	-1.930 ***	-4.110
Changes in preference for EVs by generation and wave [3]				
PHEV * Generation X * Wave 2	0.856 **	2.290		
PHEV * Generation X * Wave 3	0.424	1.100		
PHEV * Generation Y * Wave 2	0.071	0.230		
PHEV * Generation Y * Wave 3	-0.147	-0.470		
BEV * Generation X * Wave 2	0.450	1.060		
BEV * Generation X * Wave 3	0.262	0.590		
BEV * Generation Y * Wave 2	0.049	0.140		
BEV * Generation Y * Wave 3	0.068	0.200		
Changes in preference for EVs by city size and wave [3]				
PHEV * Living in small city * Wave 2			1.830 ***	3.710
PHEV * Living in small city * Wave 3			1.704 ***	3.450
PHEV * Living in big/midsized city * Wave 2			-0.272	-1.010
PHEV * Living in big/midsized city * Wave 3			-0.520 **	-1.890
BEV * Living in small city * Wave 2			1.087 **	2.010
BEV * Living in small city * Wave 3			1.327 **	2.300
BEV * Living in big/midsized city * Wave 2			-0.227	-0.740
BEV * Living in big/midsized city * Wave 3			-0.286	-0.940
Number of parameters	41		41	
Observations	7,098		7,098	
Log-likelihood of MXL at convergence	-5604.00		-5594.00	
Log-likelihood of MNL at convergence	-7093.03		-7063.75	
McFadden pseudo R-squared	0.264		0.265	
Log-likelihood ratio test versus the baseline model	7.100 (p=0.526)		27.10 (p<0.001)	

Note: *** p < 0.01, ** p < 0.05, * p < 0.10, all in one tail.
Sample is reweighted according to the actual proportion of urban population in each city tier, following Ministry of Housing and Urban-rural Development of China, which provides urban population data for each prefecture city (www.mohurd.gov.cn/xytj/tjzljsxytjgb/jstjnj/w02019012421874448287322500.xls). The actual ratio of urban population in each tier of city: first-tier (12.37%); second-tier (8.83%); third-tier (48.25%); fourth-tier (23.53%); fifth-tier (7.01%).
[1] ICEV is the reference alternative for ASCs.
[2] Lottery-based licensing as the base category.
[3] Wave 1 as the reference year.
[4] Generation Y as the base category.
[5] Living in big and midsized cities as the base category.

In comparison, Model 4 reveals the different changes in consumer preferences for EVs across different sizes of cities. As shown in Table 5, Model 4 is significantly better than the baseline model, as indicated by the greater log-likelihood function ($\chi^2 = 27.10$, $df = 6$, $p < 0.001$), which means the inclusion of interaction terms by both wave and city size can significantly improve model performance. In Model 4, most estimated parameters for EV attributes and demographic variables remain robust, as in the baseline model. Importantly, we find that, with Wave 1 as the reference time point, consumers in small cities were becoming more positive towards both PHEVs and BEVs in Wave 2 and Wave 3, in spite of the significant and negative preferences for both types of EVs in small cities in the base year of Wave 1. Particularly, in the case of BEVs, the interaction term for those living in small cities are highest in Wave 3 (β = 1.327, t = 2.30), followed by Wave 2 (β = 1.087, t = 2.01), implying a growing preference for BEVs in small cities over time. In midsized and big cities, however, most estimates of interaction terms by both city size and wave are not significantly different from zero, except the interaction between PHEVs and Wave 3. In summary, consumer preferences for BEVs were getting stronger in smaller cities, but consumer preferences for EVs in midsized and big cities were relatively stable across the three waves.

Chinese consumers in bigger cities have been widely exposed to EVs much earlier than those living in midsized or small cities. Huang and Qian (2018) show that five leading Chinese cities in EV sales in 2016 were consistently first tier ones with more than 10 million urban population each (i.e., Beijing, Shanghai, Shenzhen, Tianjin and Guangzhou). Our finding that BEVs were getting more attractive in small cities in 2018 and 2019 may relate to several specific events in the market in 2017 and 2018. First, compared to in 2016, more new EV models were included in the Chinese government's filing directory for EVs in 2017. EVs must be listed in the filing directory to be eligible for the various incentives. Specifically, there were only 22 new EV models approved in 2016, but the number sharply increased to 54 new models in 2017 (Ways, 2018). Particularly, some of the best-selling small-size or lower priced EVs were available in

2017 and 2018, such as Baojun E100 priced less than 70,000 CNY (about US$10,000). This means that not only there were more EVs but also there were more affordable ones available in smaller cities after 2017. Second, the Chinese government officially implemented the "dual credit policy" for EVs and energy saving cars in April 2018 (International Council on Clean Transportation, 2018; Wood Mackenzie, 2018). This major policy change in the market has received massive media exposure thus raised consumer attention towards EVs. We found that the Baidu search index for the keyword of "dual credit policy" (双积分) experienced a spike in late September to early October of 2017. Compared to consumers in bigger cities who had been widely exposed to EVs in earlier years, the launch of this major EV policy enabled consumers in smaller cities to get more information about EVs in late 2017 than before, which may arouse their interests for EVs in our subsequent data collection in 2018 and 2019.

5. Discussion and Conclusions

By taking a longitudinal approach, this study explores the value of studying dynamic consumer preferences for EVs – a topic that has been overlooked in the literature. We illustrate the importance of such an approach in the context of China, where both growth and adoption of EVs is heterogeneous. Using a three-wave SP experiment design and applying discrete choice modelling, we examine the changes in consumer preferences for EVs and several EV-related product/service and policy attributes. In addition, we explore the different changes in consumer preference for EVs across different generations and city sizes. We summarize our key findings, theoretical contributions and managerial/policy implications in Table 6. Below, we detail the contributions of this study.

Table 6: Summary of key findings, theoretical contributions and managerial implications

Research Questions	Findings	Theoretical Contributions	Pollicy/Managerial Implications
(1). How do consumer preferences for EVs and key attributes change over time?	• Overall, we find that Chinese consumers had stronger preferences for EVs in 2018 (wave 2) than in both 2017 (wave 1) and 2019 (wave 3). • Chinese consumers became less sensitive to running cost in 2018 and 2019 than in 2017. • Chinese consumers were consistently valuing home charging capability and prioritized vehicle licensing for EVs over the three years • The perceived importance of the density of fast charging stations fluctuated over the studied period of three years.	• We extend the EV adoption literature by demonstrating the value of employing a longitudinal approach to examine the potential changes or stability in consumer preferences for EVs. • Specifically, our work enhances the sustainable transition literature by showcasing the complex process of sustainable transition illustrated by our finding of stronger preferences for EVs in wave 2 than in other two waves. • We complement existing applications of innovation diffusion theory (Rogers, 2003), as we demonstrate in the EV context that it is important to examine the features of innovations from a dynamic and evolving perspective, including relative advantage (e.g., running cost), complexity reduction (e.g., home charging and prioritized vehicle licensing) and the observability aspects (e.g., density of fast charging).	• Policy makers and business practitioners should embrace a dynamic and forward-looking perspective when studying the effectiveness of various policy and business interventions. • Given growing and persistent concerns about home charging, it is important to develop a concrete plan for residential compounds to accelerate the installation of charging facilities for EV owners. • The fluctuating preferences for fast charging suggest the importance of coordinating the scale and speed of developing fast charging infrastructure with that of the EV penetration.

Table 6: Summary of key findings, theoretical contributions and managerial implications

Research Questions	Findings	Theoretical Contributions	Pollicy/Managerial Implications
(2). How does the consumer preference for EVs change differently across different consumer segments over time?	• Chinese consumers in small cities were developing stronger preferences for battery EVs in 2018 and 2019 than in the base year of 2017. Those living in midsized and big cities did not change their preference towards battery EVs over these three years.	• We enrich the sustainable transition literature and support the main contentions of that body of work by showing the diverse changes in consumers' preferences for EVs across different segments. Specifically, we highlight the importance of place-specific factors (i.e., geographic characteristics), an overlooked aspect in the sustainable transition literature (Bohnsack, 2018).	• Our results highlight the importance of contextualising and adapting local policies of the government over time. The strategies of car makers should follow the same approach by developing more relevant products to meet specific needs of consumers in different segment markets.

5.1. Theoretical Contributions

Our theoretical contributions are threefold. First, we extend the EV adoption literature by demonstrating the value of employing a longitudinal approach to capture the evolving nature of consumer preferences during the diffusion process over time. Specifically, our work enhances the sustainable transition literature by empirically illustrating the dynamic and complex process of sustainable transition. We find that consumers show stronger overall preferences for EVs in Wave 2 than in other waves, which not only supports the notion that sustainable transition is a non-linear process inevitably occurring from the interplay of development in socio-technical system (Geels, 2002) but also predicts the non-linear development of the actual EV market between 2017 and 2019 in China due to market and policy changes (with 63% increase in EV sales in 2018 followed by 3% decrease in 2019). Thus, the non-linearity effects observed in our research underline the premise that the diffusion of sustainable innovations should not be simplified as a linear and smooth process over time.

Second, our study complements existing applications of innovation diffusion theory (Rogers, 2003), as we explicitly demonstrate that the features of innovations, such as relative advantage, complexity reduction and the observability aspects of EVs, should be examined from a dynamic and evolving perspective. More specifically, across the three waves, consumers' sensitivity to the running cost of EVs, the relative advantage factor, was decreasing. Therefore, our analysis highlights that the relative advantage feature of innovations – as proposed by the diffusion theory (Rogers, 2003) – is dynamic. Furthermore, our results reveal that consumers have been consistently valuing the importance on ease of charging EVs at home over the three years. Such perceived inconvenience suggests that the importance of complexity reduction another feature as per Rogers's (2003) innovation diffusion theory, is not achieved naturally in the diffusion process, but should be monitored and pursued over a long period. Moreover, consumers' sensitivity to the density of fast charging stations is found to be more prominent in Wave 2 than in other waves. Such non-linear pattern indicates that consumers were paying more attention to the relative availability of public fast charging infrastructure in Wave 2. Therefore, our results demonstrate the dynamic role of the observability feature of innovations in their diffusion process (Rogers, 2003).

Third, we enrich the sustainable transition literature by revealing the diverse changes in consumers' preferences for sustainable innovations across different segments. Drawing on the sustainable transition literature (e.g., Hansen and Coenen, 2015; Bohnsack, 2018), the diverse changes in consumer preferences for EVs across cities with different sizes highlight the importance of the place-specific factor (i.e., geographic characteristics), an overlooked aspect in sustainable transition (Bohnsack, 2018). We find that those living in small cities are gradually becoming more open to BEVs, but there is no significant preference change for EVs in midsized and big cities. By highlighting the importance of place specific factors, our empirical results largely corroborate Bas et al. (2021) who find the county in which the respondents live is the most important factor associated with one's propensity to adopt an EV. While Huang and Qian (2018) found consumers from third-tier cities were less open to EVs than those from second-tier cities in south Jiangsu region of China in 2016, our study introduces the temporal dimension into the analysis and reveals the complex nature of changes in consumers' preference for EVs across cities in different sizes. This also therefore provides empirical evidence to illustrate the complexity of the geographic dimension of the dynamics of sustainable transition over time.

5.2. Policy and Managerial Implications

Our study provides important implications for policy design and actionable insights for companies and policy makers on how to accelerate the adoption of EVs and other sustainable innovations in general. Our empirical analysis demonstrates the need for intensive collaboration – including sharing of insights into the evolving state of the market – among EV manufacturers, service providers and local government agencies (Bas et al., 2022), in several ways to meet consumers' needs and wants.

First, the dynamic non-linear preferences for EVs over the three waves suggest that policy makers and business practitioners should embrace a dynamic perspective when studying the effectiveness of various policy and business interventions. Due to the uncertainties of innovations such as EVs (Silvia and Krause, 2016), a longitudinal approach can effectively reveal dynamic and non-linear preferences during the innovation diffusion process, which could offer valuable insights related to how policies and business strategies should be adapted and made responsive to different facets of the market at different points in time. This is particularly relevant in the context of our study, the Chinese car market, where, if we consider government intervention for example, different types of policies are in place in different city tiers; our work indicates that such interventions need to be continuously evaluated and adapted during EV diffusion. Similarly, for car manufacturers, the market environment and competition are changing constantly, and business strategy making involves forecasting the future state of the car market. Our proposed research approach would be helpful for business decision makers to account for the dynamics of consumer preferences and continuously update strategic making and planning along the innovation diffusion process.

Second, the dynamic consumer preferences for key attributes also suggests important new policy and managerial implications. For example, given growing and persistent concerns about the availability of home charging posts across the three waves, it is important to develop a concrete plan for existing residential compounds to accelerate the installation of residential charging facilities for EVs. Also, urban planning must consider the rising number of EVs to enable parking spaces in new residential compounds to be equipped with or reserve room for charging facilities in the future. In particular, given the typical concerns from property managing firms on EV charging (Wang, 2015; Yang, 2016), the grid should enhance energy supply to residential compounds to meet the increasing demand for home charging, and local governments should work with leading firms to develop residential charging guidelines and safety supervision processes (Bas et al., 2022). More recently, sharing private charging posts with more EV users in the same residential compound has emerged as a new solution to enhance the usage efficiency of limited charging facilities of established communities (Wang, 2022). In addition, the fluctuating preferences for fast charging suggest the importance of coordinating the scale and speed of developing fast charging infrastructure with that of the EV diffusion.

Third, and more importantly, we find that consumers from small cities are gradually becoming more open to BEVs, and several small cities in China are experiencing strong growth of EV sales (Ways, 2018). This highlights the importance of contextualising local policies from the government as well as the product design from carmakers to meet specific consumer needs and wants. For example, the successful case of Liuzhou, a third-tier city in Southwest China, is worth highlighting here. In this city, the market share of EVs reached close to 30% in 2020, more than five times China's average in that year, and thus this city was named the electric car capital of China (Bloomberg News, 2021). The city's government prioritised developing EV-related infrastructure such as the EV charging network, and worked closely with the local carmaker (i.e., SAIC-GM-Wuling) to design, develop and promote small-sized EVs (i.e., Baojun E100) based on not only local road and parking conditions, but local residents' driving habits, with daily commuting distances typically less than 30 kilometres (Kaur, 2021). Liuzhou was also very good at engaging consumers when developing its EV market. The city's government and local car maker jointly initiated a 10-month new EV test drive campaign in 2017 to increase consumer awareness about EVs and collect users' recommendations on improving the vehicle and its convenience (Cui and He, 2019).

5.3. Limitations and Future Research Directions

The limitations of this study suggest areas for future research. First, our analysis reveals a non-linear pattern of consumer preferences for EV attributes over time, but we did not conduct further analysis to evaluate and quantify the long-term relationship. Future research could also further account for the dynamics of consumer preferences for EVs, and towards sustainable innovation in general. Second, we conducted three waves of primary data collection in the form of an SP experiment. Future research could collect secondary data on the changes of market conditions and policies over time, and apply econometric models to quantify the dynamics of institutional and market factors in relation to dynamic consumer preferences. Third, our current study captures the dynamic preferences for key EV attributes and heterogeneous preferences across different demographic groups. Future research may specifically explore how the dynamic preferences for key EV attributes might be heterogeneous across different city sizes and generations. Fourth, we include only systematic variation terms for EV attributes across waves in our full sample analysis. As the Chinese EV market is characterised by a high level of within-market heterogeneity, future research could explore the dynamic preferences for EVs attributes within specific market segments (e.g., small cities) with greater potential to drive future EV market growth. Last, the SP experiment methodology is subject to hypothetical bias since information gathered is not based on real choices (Bas et al., 2022). Thus, future research may explore dynamic consumer preferences for EVs by using alternative methods such as interpretable machine learning approach (Bas et al., 2023) to improve not only the predictability but also interpretation on preference changes when adopting EVs over time.

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