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Eliciting students' stated preferences between alternative car powertrains to forecast electric car uptake in Italy and China: An application of discrete choice and agent-based models

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Abstract

Electric vehicles (EVs) are expected to play an important role in reducing carbon emissions and environmental problems in the car market. Consumers' preferences play an important role in EVs uptake. In this study, we have compared consumers' preferences regarding car choices in Italy and China to discover differences and commonalities by integrating vehicle attributes (e.g., price and range) with socioeconomic and latent variables. We carried out a stated choice experiment and collected data on a sample of Italian (N= 436) and Chinese (N= 358) respondents using a web-based questionnaire from March to November 2021.

The discrete choice model is the principal methodology in our research, and we developed a hybrid mixed logit model to explore the roles of attitudes. We have found that the attributes of the purchase price and driving range are significantly important in the potential purchase in both countries. Heterogeneity preference existed in our samples. Italians are more range sensitive. Specifically, the availability of garage charging has a significant positive effect on the choices of EVs. According to our analysis, all the latent variables used in our research have a statistically significant impact on the choice of EVs. In particular, charging awareness is stronger among Italian EV buyers than Chinese EV buyers. The findings imply that policymakers should consider heterogeneous preferences in intervention policies regarding the EV market.

In order to simulate the potential adoption of EVs in Italy and China, we have employed an agent-based model (ABM) to identify how policy instruments simulate the diffusion of EVs. Three policy implications were carried out in the simulation scenarios: price decrease, driving range increase, and price and technological improvement simultaneously. The increased driving range of BEVs in both countries plays a significant driving force for the uptake of BEVs in the following decades. Although some technological barriers still exist in the current stage, our model simulation implies that incentive promotion simultaneously on price and range could significantly affect EV uptake over a single policy.

Keywords

Stated preference; Discrete choice model; Agent-based model; Electric cars; Comparison study; Model application

Contents

List of Abbreviations

ABM	Agent-based Model
ACEA	Automobile Manufacturers' Association
AFID	Alternative Fuel Infrastructure Directive
AFV	Alternative Fuel Vehicles
ASC	Alternatives Specific Constants
ASCLM	Alternative-Specific Constant Logit Model
AVC	Asymptotic Variance-Covariance
AVE	Average Variance Extracted
BEV	Battery Electric Vehicle
BNL	Binomial Logit Model
CAAM	China Association of Automobile Manufactures
CBC	Choice-Based Conjoint Analysis
CFA	Confirmatory Factor Analysis
CFI	Comparative Fix Index
CMPS	Ministry of Public Security of the People's Republic of China
CN	China
CNG	Compressed Natural Gas Vehicles
CO2	Carbon Dioxide
CPCA	China Passenger Cars Association
EFA	Exploratory Factor Analysis
EV	Electric Vehicle
EVCIPA	China Electric Vehicle Charging Infrastructure Promotion Alliance
GEV	Generalized Extreme Value
HCM	Hybrid Choice model
HEV	Hybrid Electric Vehicles
HMXL	Hybrid Mixed Logit model
HOV	High-Occupancy Vehicle
HOV	High-Occupancy Vehicle
ICEV	Internal Combustion Engine Vehicles
ICLV	Interacted Latent Variables Model
IEA	International Energy Agency
IIA	Independence of Irrelevant Alternatives
IID	Independent and Identically Distribution
ISTAT	Italian National Institute of Statistics
IT	Italy
KMO	Kaiser-Meyer-Olkin
LC	Latent Class Model
LPG	Liquefied Propane Gas Vehicles
ML	Maximum Likelihood

MNL	Multinomial Logit model
MXL	Mixed Logit model
NFI	Normed Fit Index
NL	Nested Logit Model
NMNL	Nested Multinomial Logit Model
PAF	Principal Axis Factor
PAF	Principal Axis Factor
PCA	Principal Component Analysis
PCT	Personal Carbon Trading
PHEV	Plug-in Hybrid Electric Car
PLS	Partial Least Squares
RMSEA	Root Mean Square Error of Approximation
RMSR	Root Mean Square of Residual
RP	Revealed Preference
RPL	Random Parameter Logit Model
RUM	Random Utility Maximization
SEM	Structural Equation Modeling
SLR	Systematic Literature Review
SOC	State of Charge
SP	Stated Preference
TCO	Total Cost of Ownership
TDC	Tradable Driving Credit
TLI	Tucker-Lewis Index
UCC	Utility Controlled Charging
UNRAE	Unione Nazionale Rappresentanti Autoveicoli Esteri
WTP	Willingness To Pay
ZEV	Zero Mission Vehicles

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1. Introduction

1.1. **Background**

The transportation sector is one of the primary users of fossil fuels. Road transportation has accounted for about 75% of transport demand in the past two decades (IEA, 2022). Electric vehicles (EVs) [1], recognized as one the environmentally friendly technology products, can reduce carbon emissions in the automobile sector and the dependency on fossil fuels in the transportation sector. However, due to the different product attributes, customers have shown diverse concerns regarding EVs, and the market development has also taken place in different stages. In 2022, the registration market share of battery electric vehicles (BEVs) in the EU passenger car market reached 12.1%, an increase of more than 3% compared to 2021. However, the market share of sales on EVs in Italy was only 3.7%, which was the only big country in the European Union, and fell 27% year-on-year (ACEA, 2023). In comparison, the market share of BEVs in the sale of passenger cars in China is 22.8%, much higher than in 2021(CAAM, 2022).

Sustainable policy instruments have been employed in the EVs market around the world, including the reduction of the purchase price, tax exemptions, promotion of electric mobility, accessible charging infrastructure, free lanes, and more lenient parking policies (Coffman, Bernstein, & Wee, 2017; Liao, Molin, & van Wee, 2017). Substantial government incentives are provided to BEV buyers in Italy; for example, the “Ecobonus” policy implemented by the Italian government in 2021 provides up to €8,000 in incentives for new cars with CO2 emissions of lower than 290 g/km (ACEA, 2022b). Most recent studies have confirmed that policy instruments providing financial incentives are more effective in the uptake of EVs (Danielis, Rotaris, Giansoldati, & Scorrano, 2020; X. Huang & Ge, 2019). Moreover, the increased sales of EVs are driven by not only financial benefits but also the availability of charging infrastructure with proper functions and wide geographical distribution (Haustein, Jensen, & Cherchi, 2021). Although the charging infrastructure and vehicle technologies have greatly improved in recent years, the limited driving range is still considered a significant barrier affecting the adoption of BEVs (Liao et al., 2017). Besides, some studies have also researched individual-specific factors. These studies have considered consumer preferences concerning psychological characteristics and attitude constructs. Some researchers have also identified social norms and symbolic factors in their studies. Cherchi (2017) included social adoption in a stated choice experiment to measure the injunctive norms. Y. Huang and Qian (2018) found that enhancing social norms and face consciousness can incentivize the reorganization of EVs.

Individuals would change their behaviors or even give a wrong answer through the actions of groups, as their awareness would be driven by government and market-oriented policy instruments (Cherchi, 2017). Several studies have performed

[1] The term EVs in our paper includes only battery electric vehicles (BEVs) and focuses on the passenger car market.

stated choice experiments to understand customers' preferences in car choices. These studies are focused on stated preference and used discrete choice modeling technology to estimate choices changed (Danielis, Giansoldati, and Rotaris (2018); Danielis et al. (2020); Rotaris, Giansoldati, and Scorrano (2020); Scorrano and Danielis (2021a); Scorrano, Danielis, and Giansoldati (2020)). Moreover, in Italy, Rusich and Danielis (2015) estimated alternative automotive technology cars' private and social costs. They confirmed the high cost of BEVs in the preliminary electric market. More recently, Danielis et al. (2018) and Scorrano et al. (2020) developed research on the ownership cost of BEVs. They have confirmed decisive roles in the choice of BEVs, which include purchase subsidies, home charging infrastructure, and availability of parking facilities have played. Moreover, national security benefits and free licensing policy were confirmed as specific factors in the Chinese market (Helveston et al., 2015; Qian, Grisolía, & Soopramanien, 2019).

1.2. Car market comparison between Italy and China

To our best knowledge, only a few studies compared car choices across countries. They are mainly focused on European countries. For example, Noel, de Rubens, Kester, and Sovacool (2020) compared the barriers related to the range, price, charging, and knowledge of BEVs in five Nordic countries: Denmark, Finland, Iceland, Norway, and Sweden. Haustein et al. (2021) used principal component analyses to research users' attitudes and driving behavior compared to non-users of BEVs in Denmark and Sweden. As far as we know, only two studies have compared BEVs' car choices in Italy and other countries based on a stated preference (SP) survey. Scorrano, Giansoldati, and Andreas Mathisen (2019) compared the total ownership costs of BEVs to other alternative fuel vehicles between Italy and Norway. Rotaris et al. (2020) compared the impact of environmental awareness and BEV knowledge on car choices in Italy and Slovenia. A few comparative studies were also conducted in China and other countries. Helveston et al. (2015) used the choice conjoint method to compare China and the US car market in 2012–2013. Jeon, Yoo, and Choi (2012) conducted a survey to compare the difference in purchase intention between Korea and China.

1.2.1. Similarities of the Italian and Chinese car markets

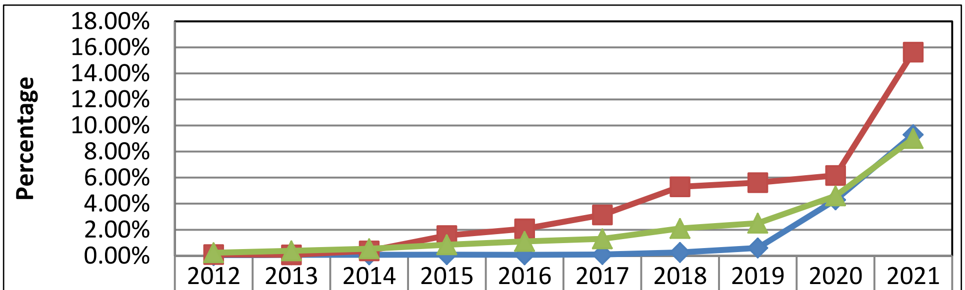
Many car drivers in Italy and China still prefer petrol- and diesel-fueled engine cars (Danielis et al. (2020); Giansoldati, Rotaris, Scorrano, and Danielis (2020); Qian et al. (2019); Scorrano and Danielis (2021c); She, Sun, Ma, and Xie (2017). They are both dominated by fossil-fueled cars; the EVs market has been modestly steadily growing since 2020.

Moreover, the governments in both countries have implemented more incentive policies for EV purchases, including tax deductions, price subsidies, and charging incentives. Sustainable policy instruments have been employed in the EV market worldwide, including reducing the purchase price, tax exemptions, promoting electric mobility, accessible charging infrastructure, free lanes, and more lenient parking policies (Coffman et al., 2017; Liao et al., 2017). Substantial government incentives are provided to BEV buyers in Italy; for example, the “Ecobonus” policy in 2021 provides up to €8,000 in incentives for new cars with CO2 emissions lower than 290 g/km (ACEA, 2022b). Most recent studies have confirmed that policy instruments providing financial incentives are more effective in EV uptake (Danielis et al., 2020; X. Huang & Ge, 2019).

In addition, EVs' increased sales are driven by financial benefits and the availability of charging infrastructure with proper functions and wide geographical distribution (Haustein et al., 2021). Although the charging infrastructure and vehicle technologies have greatly improved in recent years, the limited driving range is still considered a significant barrier affecting the adoption of BEVs (Liao et al., 2017). Besides, several studies have also researched individual-specific factors. These studies have considered consumer preferences concerning psychological characteristics and attitude constructs. Some researchers have also identified social norms and symbolic factors in their studies. Cherchi (2017) considered social adoption as an attribute in a stated choice experiment and measured the injunctive norms using psychometric indicators. Y. Huang and Qian (2018) found that enhancing social norms and face consciousness can incentivize the reorganization of EVs.

1.2.2. **Difference of the Italian and Chinese car markets**

Market share. The trendy car drivers’ preference in these two markets is different. Before 2014, the new EV sales in both countries were lower than in the world (Figure 1). After 2014, new EV sales in China increased, reaching 15.64% of the annual sales of all passenger cars in 2021(CAAM, 2022). In Italy, car drivers paid greater attention to EVs only from 2020; the share of EVs increased to 9.5% in 2021(UNRAE, 2022), the same as the average share of new sales of EVs in the world in that year.



	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
Italy	0.02%	0.07%	0.08%	0.09%	0.08%	0.10%	0.26%	0.60%	4.30%	9.30%
China	0.09%	0.08%	0.38%	1.57%	2.08%	3.14%	5.30%	5.62%	6.18%	15.64%
World	0.23%	0.38%	0.54%	0.85%	1.10%	1.30%	2.10%	2.50%	4.60%	9.00%

Note: EV cars (electric vehicle) is included battery electric vehicle (BEV) and plug-in hybrid electric vehicle (PHEV)

Figure 1 Passenger EV market share of total new car sales since 2012

New car registrations. Figure 2 lists the newly registered cars by powertrains. In Italy, for every thousand inhabitants, there are 756 cars (ACEA, 2022b). The Italian car market is considered a high-potential car ownership market, especially for small and medium-sized cars, with, as stated, limited but growing electric car uptake (Danielis et al., 2020). From the performance of the significant BEVs market in Q4 2021, Italy was the second one that posted a significant gain of BEVs in the EU (+34.9%) (ACEA, 2022a). However, it still has a lower passenger car market share (9.5%). The share of fuel cars is still high, mainly evenly distributed on petrol, diesel and HEV in Italy. In contrast, in China, there are only 219 cars per thousand inhabitants (CMPS, 2022), and the market of HEVs was only 3%, much lower than that in the Italian market. Most cars still run on fuel that is mainly petrol and diesel-fueled. As for EVs, most of the battery electric vehicles (BEVs) in China in 2015 or earlier were manufactured domestically for the lower-end market and were considered lower-quality than their international counterparts (Qian et al., 2019). In 2021, the new sales share of BEVs in the Chinese passenger car market accounted for 15.64%, higher than the world share (9%) (CAAM, 2022).

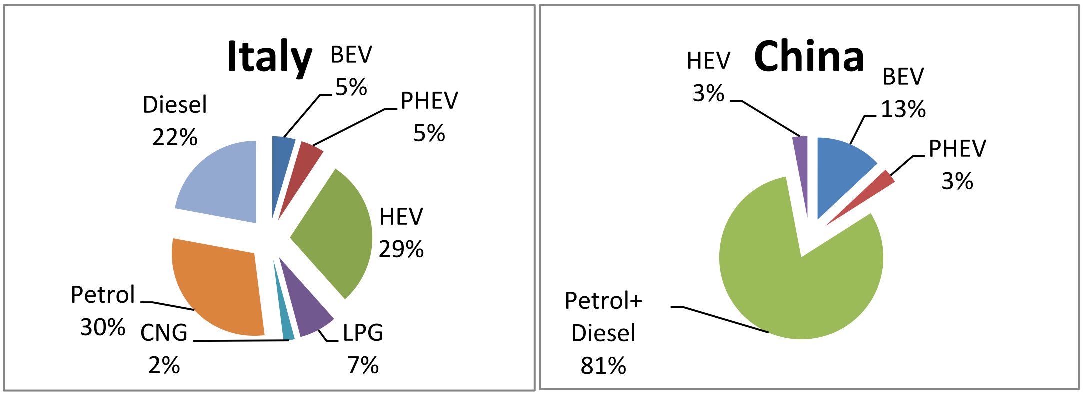


Figure 2 Car shares by powertrain of total new registered cars between Italy and China in 2021

Note: Battery electric vehicles (BEVs), plug-in hybrid electric vehicles (PHEVs), hybrid electric vehicles (HEVs), liquefied propane gas vehicles (LPG), compressed natural gas vehicles (CNG).
Sources: UNRAE (2022); CPCA (2022).

Drivers Preference. In Table 1, we have listed the top ten best-selling EVs with their respective battery size and driving range in Italy and China in 2022. We have found that Italians preferred the small segment with smaller battery capacities and shorter driving ranges. In comparison, the Chinese preferred to choose medium and more enormous segments with larger battery capacities and longer driving ranges.

Table 1 Top ten best-selling EVs in Italy and China in 2022

	Italy				China			
	Car model	Sales share	Battery size (kWh)	Driving range (km)	Car model	Sales share	Battery size (kWh)	Driving range (km)
1	Fiat 500	12.69% (6285)	42	320	BYD Song	8.0% (476,784)	71.7	505
2	Smart Fortwo	9.18% (4545)	22	132	Hongguang Mini	7.2% (423,998)	9.2	120
3	Tesla Model Y	8.63% (4276)	50.4	455	Tesla Model Y	5.3% (315,607)	60	545
4	Dacia Spring	5.70% (2825)	27.4	255	BYD Qin	5.3% (315,079)	53.1	421
5	Renault Twingo	5.56% (2742)	22	270	BYD Han	4.6% (269,691)	76.9	550
6	Peugeot 208	4.28% (2122)	50	362	BYD Dolphin	3.5% (204,674)	44.9	420
7	Mini	3.15% (1561)	32.6	145	BYD Yuan Plus EV	3.2% (190,411)	49.92	430
8	Volkswagen Id.3	3.14% (1553)	45	352	BYD Tang	2.5% (148,001)	90.3	600
9	Renault Zoe	2.91% (1442)	52	239	Tesla Model 3	2.1% (125,361)	60	556
10	Peugeot 2008	2.76% (1369)	50	214	GAC Aion Y	2.0% (119,687)	63.98	510

Source: UNRAE (2023), CPCA (2023)

EVs charging network. The level of charging infrastructure was different. The alternative fuel infrastructure directive (AFID) recommended that the average EVs to charger ratio be ten by 2020. Italy roughly meets the recommended charger ratios of 11 EVs per charger. However, the Chinese market is pulling down the global averages at 7 EVs per charger (IEA, 2023). In 2022, the public access charging points in Italy were 32,776 (MOTUS-E, 2023), whereas the Chinese charging infrastructure increased by 2.593 million. In particular, 1.797 million public charging points were reported, which increased by 91.6% year-on-year (EVCIPA, 2023).

Social influence. Social influences performed on culture and economic development were confirmed as having a significant role in consumer behavior (Jeon et al., 2012); enhancing social norms and face consciousness can incentivize the reorganization of EVs (Y. Huang & Qian, 2018). However, the cultural and economic development levels were different in the two countries. Italy is considered a developed country, whereas China is considered a developing country; according to the World Bank data in 2021, the GDP per capita in Italy was $ 31,505, almost twice as high as in China, which was only $17,734.

1.3. **Thesis outline**

Our study will focus on the effects of EV adoption factors and attitudes between Italy and China. We will examine the similarities and differences between prospective buyers of electric vehicles (EVs) and try to identify changes in the determinants of car choices between battery electric vehicles (BEVs) and other fueled cars[2].

The structure is as follows. In chapter 2, we gave a general literature overview related to stated preference in recent five years. In chapter 3, we listed the main methodologies and modeling framework, including the multinomial logit model (MNL), mixed logit model (MXL), and hybrid choice model (HMXL). In chapter 4, we carried out our first experiment and have a description of the samples and results. In chapter 5, we listed our stated preference experiment, described the new sample experiments in detail and listed the results of exploratory factor analysis (EFA) and confirmatory factor analysis (CFA). In chapter 6, we presented the econometric results of MNL, MXL, and HMXL models. In chapter 7, we implemented the model application based on our econometric results. In chapter 8, we have developed an agent-based model to simulate the potential uptake of EVs, parameterized with data derived from our choice survey in Italy and China. Finally, conclusions and future work are listed in section 9.

[2] The fueled cars in our paper included petrol cars, diesel cars, plug-in hybrid electric vehicle (PHEV), hybrid electric vehicle (HEV), liquefied propane gas (LPG), compressed natural gas (CNG), we made a general reference as internal combustion engine vehicles (ICEVs).

2. Literature Review

2.1. **Introduction**

In recent years, many studies on the adoption of EVs have been conducted, with the majority focusing on objective aspects, such as financial and technological attributes, showing significant effects on customers' choices. Individual-related variables are also investigated in preference studies; however, individuals may reevaluate their preferences when confronted with novel market influences.

In this chapter, we aim to answer the following questions by proposing a conceptual framework for EV preferences based on research conducted over the past five years: How are preference studies structured? What are the main methodologies applied in these studies? What are the key identified characteristics? How much may these variables affect consumers' decisions? In section 2.2, we have defined EVs' classification and discussed the database in detail. In section 2.3, we have described the modeling methodologies on EVs in stated preference reviewed studies. Then we have categorized the various attributes of EVs (section 2.4). Finally, we have given a summary to present the main findings and conclusions (section 2.5).

2.2. **Reviewed method and database in stated preference studies**

In general, according to the different propulsion systems, vehicles are divided into internal combustion engine vehicles (ICEV) and alternative fuel vehicles (AFV). ICEV is powered by energy-dense fuels, such as petrol, diesel, gasoline, and liquids. AFV is a motor vehicle that uses alternative fuels rather than traditional petroleum fuels (petrol or diesel). The electric vehicle is one of the AFVs that are entirely powered by an electric motor; the batteries are the only energy source. Our research focuses on battery electric vehicles (BEVs) and passenger automobile markets.

We used the systematic literature review (SLR) method to select the relevant research papers. Two steps were identified in our research. The first step was started by using a search engine and databases. We have chosen Scopus and Elsevier as our main search engines; the keywords used were electric vehicles paired with stated preference and choice models, and the papers published were from 2015 to 2020. The language we chose was English, and the papers were required to be published by the journals in a definitive form. Non-English papers and papers still in the process were excluded. Based on these rules, we have chosen 84 related papers. The second step was conducted by a manual review process. According to the brief abstract and research structure, 38 papers were excluded, and finally, we have got 46 papers. It is worth noting that the database we have chosen is also being updated; the current number of studies might differ from the time we have carried out the review process.

2.3. **Modeling techniques description in stated preferences studies**

Two preference techniques are used in the transportation field: revealed preference (RP) and stated preference (SP) (Kroes & Sheldon, 1988). RP is based on data from the observation of direct travel behavior or actual travel behavior. However, obtaining all the variables with sufficient variation with this method is difficult. In SP, the respondents' choices among a set of transport options are used to analyze their preferences. The transport options are presented in hypothetical transportation contexts, which are described by researchers. Based on the collected choice data, explicit modeling of different individual preferences is performed. The widely used methodology for this is discrete choice modeling, wherein the selection option of which car a person buy is related to vehicle characteristics or attributes of each available car; the models estimate the probability by using taste parameter values (Liao et al., 2017). Since SP data can predict the demand for new products in emerging markets, they have become standard practice in new vehicle technology studies (Louviere, Hensher, & Swait, 2000). In our reviewed studies, we will focus on the SP modeling technique, rely on hypothesized situations, and use the stated-choice method to analyze preferences because of the immature EV market. Table 2 lists the summarized studies, including their main methodologies. Table 3 summarizes the characteristics, including advantages and disadvantages of the mainstream modeling technologies.

2.3.1. **Multinomial Logit model (MNL)**

The techniques for modeling SP choices assumed random utility maximization. The most frequently used form is the MNL model; a large number of researchers have used this model in their studies, for example, Rotaris et al. (2020), Danielis et al. (2020), Giansoldati, Rotaris, et al. (2020), Scorrano and Danielis (2021a), Ling, Cherry, and Wen (2021), and Qian et al. (2019). 13 papers have mentioned this model as early pioneering efforts in their researches. It is assumed that each error term follows an independent and identical distribution as extreme value type I, with fixed coefficients among individuals. The choice probability form in the MNL model is listed as follows.

$$P_{qj} = \frac{\exp(V_{qj})}{\sum_{j=1}^{J} \exp(V_{qj})}$$

However, the property of independence of irrelevant alternatives (IIA) is considered constraint imposed by the MNL model; researchers cannot capture all sources of correlation over alternatives, and it is difficult to evaluate the preference heterogeneity using the model (Train, 2009).

More generalized extreme value (GEV) models appeared. Unobserved portions of utility for all characteristics evaluated as a generalized extreme value distribution are the unifying attribute in GEV models. The most used model is the nested logit (NL) model, which is derived from the MNL model and designed to account for random preference heterogeneity (W. H. Greene & Hensher, 2003). 18 research papers have used the latent class (LC) model as their main methodology. Multiple options exist for each individual in the NL model, which are correlated with various observations. It is a method to identify various factors which are most likely to influence the adoption of EVs by individuals; it has relaxed the IIA restrictions and provided a rich set of substitution patterns. Nests in the NL model are subsets when decision makers are presented with a set of alternatives. When there are two choices in different nests, the probability ratio is reliant on the characteristics of the other alternative; hence, the IIA restriction is ineffective. Hahn, Lee, and Choi (2018) employed the NL model to describe the choice situations and behavior patterns of BEV drivers under charging conditions. Y. Huang and Qian (2018) used three nest logit models to describe all potential relationships between the alternative specific constants (ASCs) of PHEVs and BEVs. Gomez Vilchez et al. (2019) used a “low-emissions” nest multinomial logit model to estimate the maximum utility of hybrid and zero-emission cars. However, taste parameters are fixed constants in the nest logit model, it can easily neglect the varied preferences among individuals.

2.3.2. **Mixed logit model (MXL)**

The mixed logit (MXL) model has emerged as a more robust alternative model for addressing individual heterogeneity and random decision variations. The functional form is determined by the likelihood of its choice, which pursues random utility maximization (RUM) (Ashkrof, Homem de Almeida Correia, & van Arem, 2020). 13 reviewed papers have used the MXL model in preference-related studies. For the mixed logit model, the random taste of coefficients follows a continuous random distribution across respondents (Ge, MacKenzie, & Keith, 2018).

Some researchers used a random parameter logit (RPL) model because the preference parameters varied across individuals (Danielis et al., 2020). In addition, the random parameter can explain the unobserved heterogeneity of individual preferences among observations. In particular, the corresponding value of parameters can be approximated by assigning coefficients to a specific distribution. Error components in the mixed logit model represent correlations among various utility options. It can be utilized without the random coefficients interpretation (Train, 2009). By using a mixed logit model with an error component, some researchers have explored respondents’ heterogeneity with fluctuating levels (Cherchi, 2017; de Luca, Di Pace, & Marano, 2015; Gu, Yang, Feng, & Timmermans, 2019; Guerra, 2019; Rudolph, 2016; Ten Have, Gkiotsalitis, & Geurs, 2020; X. Yang et al., 2017).

Taking socio-demographics and vehicle characteristics into account, Cirillo, Liu, and Maness (2017) used a mixed multinomial logit (MXL) model to predict vehicle preferences for gasoline, hybrid electric, and battery electric vehicles in the American market. In addition, the MXL model can also focus on panel data correlation, that is, “contextual correlation” between multiple individual choices in the repeated selection context. Higgins, Mohamed, and Ferguson (2017) used the mixed multinomial logit model to examine the variation among different vehicle segments based on the panel dataset of vehicles. Qian et al. (2019) developed a panel random-utility model to examine willingness to pay (WTP).

In addition, some researchers have used alternative specific constants (ASC) in the utility function to capture the combined characteristics of alternatives that are not included in selection experiments. Specifically, the alternative specific constant is interpreted as a primary preference for EVs when the other attribute levels are the same. Sheldon, DeShazo, and Carson (2017) used a logit model with an alternative specific constant (ASC) to examine the relationship between customer characteristic tastes and preference parameter distributions. However, as attribute levels are implemented in different studies, it is not possible to compare directly the interaction of alternative specific constants used in different research (Liao et al., 2017).

2.3.3. **Hybrid choice model (HCM)**

Some researchers have further explored the hybrid choice model (HCM) to incorporate objective attributes and psychological characteristics. Jensen, Cherchi, and Mabit (2013) and Cherchi (2017) investigated the vehicle attributes, environmental concerns, and social conformity on the preference of EVs by using the HCM. Sottile, Meloni, and Cherchi (2017) estimated the latent effects of social norms, environmental attitudes, and stress on HCM and confirmed the role of stress in promoting sustainable mobility. More recently, Rotaris et al. (2020) and Giansoldati, Rotaris, et al. (2020) have considered the car knowledge of respondents and environmental awareness in the Italian electric car market and incorporated vehicle attributes and psychological characteristics into HCM. L. Li, Wang, and Xie (2022) investigated the significant role of personal carbon trading (PCT) in the Chinese market.

There is some more advanced application used in previous studies. Higgins et al. (2017) sed a multivariate analysis of variance model to compare multiple individual groups between variables and test variations between different segments based on the assumption that individuals with different socioeconomic, demographic, and spatial characteristics have different preferences for vehicle attribute characteristics. Jensen, Cherchi, Mabit, and De Dios Ortúzar (2017) have proposed a diffusion model to predict the diffusion effect in actual market shares by considering the real-world experience with products in long-term penetration patterns. Ma, Fan, Guo, Xu, and Zhu (2019) developed a language analysis model to extract core keywords from the text data of consumer comments in order to investigate the heterogeneity of consumer preferences.

Although these advanced models have good model fitness, no direct studies are comparing the fitness of various models; therefore, we cannot confirm with absolute certainty which is the best modeling technology (Liao, Molin, Timmermans, & van Wee, 2018, 2019). Researchers are free to select the ones that can better explain their research questions.

Table 2 The used modeling technologies in previous studies

Author(s) (year)	Country	Year	Respondents Number	Each choice tasks number	Alternatives	Estimation model
Bailey and Axsen (2015)	Canada	2013	1470	4	PHEVs (plug-in electric vehicles)	MNL (multinomial logit model),LC (latent class model)
Cartenì, Cascetta, and de Luca (2016)	Italy	2014	600	8	EVs	BNL (binomial Logit model)
Hackbarth and Madlener (2016)	Germany	2011	711	15	AFVs (alternative fuel vehicles) including NGVs, HEVs, PHEVs, BEVs, BVs, and FCEVs	MNL, LC
Y. Yang, Yao, Yang, and Zhang (2016)	China	2014	237	12	BEVs	MNL, NL (nested logit model)
Beck, Rose, and Greaves (2017)	Australia	2011	204	4	PHEVs, BEVs	MNL, Hybrid-MNL model
Cherchi (2017)	UK	2014	200	6	EVs	MXL, LM (latent variable model)
Cirillo et al. (2017)	USA	2014	456	6	HEVs, BEVs	MXL
Higgins et al. (2017)	Canada	2015	20,520	4	EVs (HEVs, PHEVs, and BEVs)	MANOVA models
Jensen et al. (2017)	Denmark	2012 and 2013	196	6	BEVs	advanced choice models with a diffusion model
Rudolph (2016)	Germany	2013	875	8	ZEVs (zero mission vehicles) include BEV, PHEV, FCEV	MXL
Sheldon et al. (2017)	USA	2013	1,261	5	PEVs include PHEVs,BEVs	MXL, ASCLM (Alternative-Specific Constant Logit Model), LC
Smith, Olaru, Jabeen, and Greaves (2017)	Australia	2015	440	6	EVs	MNL
X. Yang et al. (2017)	China	2014	302	8	Elesctric cars	MXL

D. Yang and Timmermans (2017)	Netherlands	2014	572	16	NEVs include EVs	RPL (random parameters logit model)
Ferguson, Mohamed, Higgins, Abotalebi, and Kanaroglou (2018)	Canada	2015	17,953	4	EVs (HEVs, PHEVs and BEVs)	LC
Hahn et al. (2018)	Korea	2015	4,548	6	Green vehicles (include HEVs, BEVs, PHEVs)	MNL, NL, MXL
Y. Huang and Qian (2018)	China	2015	348	6	PHEVs, BEVs	NL
Liao et al. (2018)	Netherlands	2016	1003	6	EVs (PHEVs, BEVs)	LC
Liu and Cirillo (2018)	USA	2014	456	6	EVs include HEVs	MNL,Dynamic model
Nie, Wang, Guo, and Shen (2018)	China	2014-2015	760	4	EVs	MNL, RPL
Wolbertus and Gerzon (2018)	Netherlands	2016	559	9	EVs	BNL (binomial logit model), LC
Abotalebi, Scott, and Ferguson (2019)	Canada	2015	11,539	4	EVs (HEVs, PHEVs and BEVs)	LC
Gu et al. (2019)	Austria	2017	203	8	EVs	MXL
Gomez Vilchez et al. (2019)	France, Germany, Italy, Poland, Spain, United Kingdom	2017	1,248	2	EVs (FCEVs, PHEVs and BEVs)	NMNL(nested multinomial logit model)
Kim, Lee, Park, Hong, and Park (2019)	Korea	2017	779	2	BEVs	BNL (binary choice model)
Kormos, Axsen, Long, and Goldberg (2019)	Canada	2017	2123	6	ZEVs (PHEVs,BEVs, HFCVs)	LCM, MNL
Liao et al. (2019)	Netherlands	2016	1003	6	EVs (PHEVs, BEVs)	Latent variable model
Ma, Fan, et al. (2019)	China	2016	25070	18	EVs (BEVs, PHEVs, EREV)	Language analysis model
Pan, Yao, and MacKenzie (2019)	China	2018	160	5	EVs	BL , LC

Qian et al. (2019)	China	2015	1076	6	EVs (BEVs, PHEVs)	MNL,MXL
Ashkrof et al. (2020)	Netherlands		505	4	EVs (HEV, PHEV,BEV)	MXL
Danielis et al. (2020)	Italy	2018	996	12	EVs (HEV, PHEV,BEV)	MNL,RPL
Ghasri, Ardeshiri, and Rashidi (2019)	Australia	2018	1076	8	EVs	ICLV (Interacted latent variables model)
Gong, Ardeshiri, and Rashidi (2020)	Australia	2018	1076	8	EVs	LCM
Guerra and Daziano (2020)	USA	2018	1545	12	EVs	LCM
Gu and Feng (2020)	Netherlands	2017	203	8	EVs	MNL
Ten Have et al. (2020)	Netherlands	2019	311	4	EVs	MXL
Jin, An, and Yao (2020)	China	2018	512	12	EVs	MNL
Liao, Molin, Timmermans, and van Wee (2020)	Dutch	2016	1003	4	EVs	LCM
Lu, Yao, Jin, and Pan (2020)	China	2018	900	8	BEV	BL
de Luca, Di Pace, and Bruno (2020)	Italy	2018	318	5	EVs	HCM (hybrid choice model)
Miele, Axsen, Wolinetz, Maine, and Long (2020)	Canada	2017	1884	4	ZEVs	LCM
Tchetchik, Zvi, Kaplan, and Blass (2020)	Israel	2014	309	3	EVs(BEVs, HEVs)	MXL
Zhou, Wen, Wang, and Cai (2020)	China	2018	334	3	EVs	LCM
Rotaris et al. (2020)	Italy	2018	1,934	12	EVs (HEV, PHEV,BEV)	HCM
Wang, Yao, and Pan (2021)	China		300	6	EV	BL (binary logit),LC

Table 3 Description of the mainly used models

Type	Advantages	Disadvantages
MNL model	Low technical requirement, stability robustness, high commonality	Strictly assumptions of random utility independence, ignored possible correlation between alternatives, easily to cause independence irrelevant alternatives (IIA)
NL model	Handle the relevance of alternatives properly with nest tree structure	Fixed constants for taste parameters, ignored varied preferences among individuals
MXL model	The coefficients of explanatory variables are randomly, can be used to deal with various relevance and panel data	It cannot tell which respondents have which preferences, cannot explain the heterogeneity caused by time series
LC model	It can judge whether there are significant effect between categories, avoid subjective factors in population sample segmentations	It may cause not convergence because of too many categories, the model parameter estimation is complicated

Source: Summarized according to the reviewed studies

2.4. Attributes review on preferences of EVs

In general, many studies have revealed customers' vehicle preferences. Most studies have focused on objective characteristics, including financial and non-financial attributes, significantly affecting on customers' choices. Some studies have examined the impact of policy measures on the development of charging infrastructure (Fang et al., 2020). Individual-related variables are also included in the preference studies, however individuals might re-evaluate their choices when they face new influencing factors in the market. In this section, we will present a detailed overview of preferences for different attributes of EVs. Four categories are summarized: financial attributes, non-financial attributes, policy incentives attributes, and individual-related attributes.

2.4.1. Financial attributes on preferences of EVs

Financial attributes are mostly associated with monetary variables, such as the purchase price, costs (e.g., operating cost, maintenance cost, fuel or electricity cost, energy cost, charging cost), and other factors. A recent review of consumer preferences for EVs was carried out by Liao et al. (2017), who identified the attributes that impact the choice of EVs, including vehicle attributes, infrastructure systems, and promotion policies, and confirmed the generally significant effects of financial and technical attributes on the utility of EVs. Coffman et al. (2017) also conducted a peer-reviewed study to explore the roles of policy incentives and confirmed the mixed effectiveness in encouraging EV uptake.

The *Purchase price,* regarded as the most crucial economic attribute, has played a significant role in EVs adoption (Coffman et al., 2017; Liao et al., 2017). 11 reviewed studies have mentioned this and found a significant negative sign on the utility of EVs. The relatively high purchase price is considered one of the crucial obstacles to EV uptake (Abotalebi et al., 2019; Liao et al., 2017). Users who were more concerned with the purchase price were more vulnerable to obtainable financial gains than to potential hedonic or symbolic gains (de Luca et al., 2015). Hackbarth and Madlener (2016) found that individuals who were not particularly interested in AFVs would accept substantial additional purchase price charges if the current disadvantages were reduced. In addition, several studies have examined the sensitivity of purchase prices across various business models. According to Liao et al. (2018), a leasing business strategy does not work for the "fallback" group because the purchase price is a negative but insignificant factor. Ma, Fan, et al. (2019) have confirmed that consumers are more willing to accept vehicles with higher prices and larger sizes than BEVs in medium and long-term business models. Specifically, EV prices played a decisive role in the rapid uptake of BEVs in Italy (Danielis et al., 2020). Car users in the Italian market who cared more about the purchase price were more easily captive to possible financial benefits rather than hedonistic gains (de Luca et al., 2015). Moreover, Rotaris et al. (2020) confirmed the stronger price sensitivity of the Italian respondents. In the Chinese market, medium- and long-term business models showed consumers were more willing to accept fossil-fueled vehicles with higher prices and larger sizes than BEVs (Ma, Xu, & Fan, 2019). The respondents, due to limited income, did not want to pay a higher charging fee for EVs (Wang et al., 2021). In addition, the impacts of purchase price frequently interacted with individual-related variables; we will discuss this topic in more detail in the following section.

Compared to internal combustion engine (ICE) vehicles, the *operating cost* has a significant negative affect on the market for EVs. Some studies have included fuel expenses as a component of operating costs. Using fuel economy, the researchers calculated the cost of gasoline per 100 kilometers driven in an automobile (Bailey & Axsen, 2015; Cirillo et al., 2017; Danielis et al., 2020; Ferguson et al., 2018; Kormos et al., 2019; Shin, Lim, Kim, & Choi, 2018). In addition, they considered the annual fuel cost as the dominant operating cost (Hahn et al., 2018) and evulated annual fuel costs togther with annual electricity costs in a single group (Ferguson et al., 2018). Y. Huang and Qian (2018) found that the availability of fuel or charging stations, particularly for home charging, might significantly influence respondents' willingness to pay for (WTP) fuel cost.

Many studies have examined the role of the *total cost of ownership (TCO)* of electric vehicles. Danielis et al. (2018) developed a TCO model and found that BEVs on the Italian car market was less cost-competitive than fossil-fueled cars. This is also in line with the findings of Scorrano et al. (2020). D. Yang and Timmermans (2017) considered the operating cost with energy cost and fuel cost to calculate the additional travel-related costs caused by the new energy price policies. Compared with the BEVs group, PHEV-oriented classes have a higher willingness to pay and are more sensitive to operating and refueling costs (Hackbarth & Madlener, 2016). Moreover, some studies have considered the socio-economic variables with costs to investigate the willingness of repondents. Bailey and Axsen (2015) have found older people and people with less than a bachelor's degree education would strongly reject new technology vehicles. Individuals in the economy segment paid more attention to fuel economy and maintenance costs on average (Higgins et al., 2017). Households with less than two vehicles are more sensitive to the fuel costs, and they will dirve less if fuel prices rise (Liu & Cirillo, 2018). Rotaris et al. (2020) have also confirmed fuel or electricity cost for respondents in lower-income countries would have a greater effect on the uptake of BEVs. Furthermore, people who currently have higher fuel costs or a longer parking distance are more likely to choose EV car sharing over fossil fuel cars (Liao et al., 2020).

In some of the studies, *travel-related cost* is also a significant factor in EVs choice. It has been shown that the total cost of travel time has a significant negative impact on individual decisions (Cartenì et al., 2016). Considering personal activity travel behaviors with fuel price policies, there is a direct positive effect of reducing traveling expenses on the choices (D. Yang & Timmermans, 2017), and compared with conventional cars, the total cost of ownership of EVs would be more competitive if respondents traveled farther annually (Danielis et al., 2020).

In addition, *parking cost* has a considerable impact on the decision of EVs drivers. According to Cherchi (2017), the preference for parking cost is really substantial. By modifying the parking price, such as rebates on parking fees with a maximum annual amount of $400, more drivers will be incentivized to choose EVs (Gong et al., 2020; Pan et al., 2019). In addition, the desire to pay for parking is typically related to charging time and time spent hunting for a parking spot (Guerra & Daziano, 2020).

The only factor highlighted in the study by Liao et al. (2018) was *battery lease cost*, which significantly increased the appeal of BEVs when only battery leasing was offered and was considered as a specific business strategy to encourage the substitution of conventional vehicles with those EVs. However, the impact of battery lease cost would change if the vehicle lease business model was made available for all vehicle types.

2.4.2. Non-Financial attributes on preference of EVs

Non-Financial attributes refer to characteristics that cannot be easily measured in financial terms. We have identified factors that significantly impact the adoption of EVs in the reviewed studies, including aspects related to usability, infrastructure, technical performance characteristics, and social conformity.

Usability-related attributes

Among the usability-related attributes, the role of *driving range*, which is described as the distance with a fully charged battery, is widely confirmed significantly affected the promotion of EVs. Almost all of the reviewed literature mentioned this factor, and most of the research revealed positive and significant signs in the utility of EVs (Beck et al., 2017; Cherchi, 2017; Danielis et al., 2020; Ghasri et al., 2019; Guerra & Daziano, 2020; Hahn et al., 2018; Y. Huang & Qian, 2018; Liao et al., 2018; Rotaris et al., 2020). Drivers would feel more range anxiety because of limited driving distance on smaller BEVs (Sheldon et al., 2017). However, some studies investigated that increasing fuel availability would more effective than simply extending driving range in promoting the market share of EVs (Hahn et al., 2018). In addition, Hackbarth and Madlener (2016) discovered that, although limited driving range is the major significant obstacle to electric mobility, car purchasers would not be willingness to pay for battery capacity improvement, even if they normally prefer BEVs.

In order to investigate the further influence of driving range on behavior choices, some researchers have used more detailed range attributes, such as *recharge range, cruising range, and electric range*. Driving range in a single recharge is a technology-related attribute of EVs that can affect how frequently cars need to be recharged (Ghasri et al., 2019), and recharging range has a significant impact on the uptake of EVs (Liu & Cirillo, 2018). Y. Yang et al. (2016) used cruising range under actual traffic conditions, and their findings proved that cruising range is a crucial component that affects the charging and routing behavior of drivers. In fact, it has been proven that the average range of EVs is steadily increasing, reaching an average value of 280 km, rendering drivers nearly immune to "range anxiety" (Nykvist, Sprei, & Nilsson, 2019). Individuals would not likely to buy EVs as extra vehicles if the driving range was less than 300 kilometers(Gu et al., 2019), and an excessively extended driving range that was longer than 400 kilometers was unlikely to be necessary for prospective buyers of EVs (Nie et al., 2018). This finding was also consistent with the research of Zhou et al. (2020). In addition, if users choose car-sharing solutions for their trips, respondents would not be likely to take the risk of a long-distance trip because of the short driving range of EVs (Jin et al., 2020; Liao et al., 2020).

Charging time is also recognized as an important factor to evaluate in conjunction with limited driving range by researchers in stated preference studies (Danielis et al., 2020; dos Santos, Tecchio, Ardente, & Pekár, 2021; Guerra, 2019; Tchetchik et al., 2020). Drivers have shown a strong inclination to minimize the charging or recharging time (Ghasri et al., 2019; Y. Yang et al., 2016), and if the charging time is shortened to below 30 minutes, they will increase their willingness to pay for EVs (Hackbarth & Madlener, 2016). When charging time was reduced from one hour to ten minutes, Nie et al. (2018) found that EVs buyers had a stronger preference for shorter charging time than non-EVs buyers. Respondents are also willing to pay approximately \$100 per month for rapid-charging time and approximately \$20 per month to avoid spending more than five minutes seeking for parking spots (Guerra, 2019).

In addition, the attribute of *charging time at home or public stations* is remarkable different for the choices of EVs. Abotalebi et al. (2019) confirmed that home charging time is only significant for the PEV-oriented group, wheareas ICEV- and HEV-oriented groups are sensitive to public charging time. This finding is also further supported by Ma, Fan, et al. (2019), who found that consumers pay more attention to slow charging speed than rapid charging as fast charging is only available at public charging stations. Morover, Ashkrof et al. (2020) have pointed out that waiting time for charging on a given route would reduce the utility of EVs.

Infrastructure attributes

Charging infrastructure or charging stations are recognized as one of the most influential variables affecting the utility of EVs. Users who preferred smaller vehicle body types were more concerned with the availability of charging stations. (Higgins et al., 2017), whereas the impact of station availability would decrease as vehicle size increase (Hahn et al., 2018). In addition, the density of charging infrastructure can be used to evaluate the choice state of individuals (Hackbarth & Madlener, 2016). Unbalanced distribution of charging stations would reduce the long travelling plans for individuals (Liao et al., 2018; Nie et al., 2018). However, if sufficient large-scale fast-charging infrastructures can be provided, consumers would like to choose a dense network of fast-charging stations over long distances (Abotalebi et al., 2019; C. W. Yang & Ho, 2016)

Moreover, respondents, particularly those living in flats without a separate parking space and home charging capabilities, have demonstrated a greater willingness to pay for home charging infrastructures (Y. Huang & Qian, 2018). In contrast, Pan et al. (2019) discovered that the type of charge, rapid or slow charging, and charging time would not greatly impact users' charging decisions. However, if charging station owners were able to freely control fuel pricing, this may arouse drivers' interest. In addition, respondents had minimal interest in the average charging distances between 5 km and 20 km (Gong et al., 2020). It is probable that respondents' lack of knowledge and experience with EVs prevents them from forming a definitive preference, particularly with regards to charging facilities (Miele et al., 2020).

Technical performance attributes

Compared to ICEVs, *the technology performance of EVs*, including four features of power, top speed, acceleration, fuel range, has been a controversial topic for quite a long time (de Luca et al., 2020). Rotaris et al. (2020) found that technological constraints, such as mistrust of new technology, battery disposal issues, and battery degradation risk, have a significant effect on the uptake of EVs. Improvements in fast-charging technology are crucial for extending the range of EVs (Nie et al., 2018), it could increase the adoption of EVs with shorter average ranges in the neighborhoods (Guerra, 2019). When technologies have improved, the probability for Italians to buy EVs has increased (Danielis et al., 2020). *Battery technology* is a key factor affecting the adoption rate of EVs. The quality of battery warranty are perceived positively in a significant way, especially on the PHEV-oriented group (Abotalebi et al., 2019; Higgins et al., 2017). Liao et al. (2019) have found that maintenance and warranty for BEVs can considerably minimize residual value uncertainty, which can promote the adoption of EVs. However, the battery of EVs cannot be over charged, their capacity is limited at current stage; therefore, the improvement of large battery sizes, especially for BEVs exceeding 220 miles, has become a main breaking point in the future marke (Zhou et al., 2020). In contrast, Jensen et al. (2017) found the effect of battery life were not significant on the adoption of EVs. Even if respondents had a real-life driving experience, consumers might make their choices based on market variables.

Social conformity attributes

Social conformity is a phenomena that drives individuals to act in accordance with the majority group, whether consciously or subconsciously (Crutchfield, 1955). It can reflect individual behaviors by social-signaling. Cherchi (2017) has divided the social conformity into two aspects: information conformity and normative conformity (descriptive norms, injunctive norms, social-signaling) and confirmed all the social conformity effects are highly significant. Although it is impossible to quantify the overall utility of social conformity, the high effect is enough to compensate the limitations of lower driving range and higher purchase price of EVs. Jensen et al. (2017) have confirmed the social role on the penetration of EVs market. Smith et al. (2017) also discouvered that subjective norms had a substantially greater impact on the non-trader group, and performed more like “social desirability”.

2.4.3. **Policy attributes**

Policy characteristics are identified as crucial factors in our evaluation procedure (e.g. purchase subsidies, tax reliefs or tax exemption, rapid charging stations established policy, free parking policy, free access to specific lines). Liao et al. (2017) confirmed the significant role of effective policy characteristics in the promotion of EVs. Based on the reviewed studies, we classified incentives as either financial or non-financial.

Financial-related incentives are widely researched in the studies. They generally include *price subsidy, cost reduction, cash incentives and tax reliefs or exemption***.** In particular, governmental incentives, such as rebates on upfront costs, discounts on parking fees, energy bill discounts and stamp duty reliefs, are likely to accelerate a widespread uptake of electric cars (Gomez Vilchez et al., 2019; Gong et al., 2020; Kim et al., 2019). Rudolph (2016) estimated five different tested incentives: direct subsidies, free parking, separate carbon tax, increasing tax elevation for fuel costs, and charging infrastructure availability, then found that all the five incentives can increase the attractiveness of ZEVs for respondents.

Compared with environmental incentives, cost incentives were more effective in attracting customers, especially by providing cost subsidies to PEV users (Bailey & Axsen, 2015; Cherchi, 2017). Road tax exemption, purchase price subsidies, tax exemption and fuel cost reductions are also shown to be able to strongly stimulate the demand of electric cars (Hackbarth & Madlener, 2016; Liao et al., 2019; Lu et al., 2020; Miele et al., 2020). Among these financial incentives, economic incentives, particularly cash incentives, were found to be highly positive to accelerate the diffusion of new technology vehicles in the market (Abotalebi et al., 2019; Cirillo et al., 2017; Higgins et al., 2017; Nie et al., 2018). By using alternative specific constants to capture the unobserved factors Sheldon et al. (2017) found financial incentives, such as subsidies and free single-occupant vehicle lane access, are more significant in their effects on the stimulation concerning PHEV than BEVs. Moreover, D. Yang and Timmermans (2017) have tested energy price-related policy portfolios: fuel tax, fuel-related carbon dioxide (CO2) tax, gas/electricity tax, gas/electricity-related CO2 tax, and public transportation fees, all of the energy policies have a direct positive effect on investing energy-efficient cars.

Non-financial incentives attributes also played important roles in accelerating the EVs market share. Most of the non-financial incentives are related with governmental support: *fast charging infrastructure, parking policy, free lane access, free license plates.*

Fast charging infrastructure can be considered as one of the most important incentives in the studies. This incentive is normally related with technology improvement, considered as an extremely essential and serious improvement attribute concerning the uptake of EVs (Nie et al., 2018). As charging inconvenience was the main obstacle for customers assessing with EVs (Bailey & Axsen, 2015), the provision of a widespread network of fast charging infrastructures could certainly influence customers' decisions when choosing AFVs (Hackbarth & Madlener, 2016). But the effect of charging station availability on different segments shows a significant discrepancy: people owning economy and intermediate vehicles are more easily to change their choice because of public charging stations numbers (Higgins et al., 2017). Furthermore, the distances within fast charging networks show a negative sign, as well as fast charging time (Danielis et al., 2020; Nie et al., 2018; Smith et al., 2017), indicating that consumers prefer a denser fast charging network when driving for long distances (Liao et al., 2018). However, Ma, Fan, et al. (2019) have proposed in their research the opposite finding: they found that consumers paid more attention to slow charge times than to fast charge depending on their residence, and the charging time, no matter whether slow or fast, is more important than how far the EV can run.

Parking policy is another important implemented incentive for the promotion of EVs' uptake, related with parking spaces reserved for EVs (Cherchi, 2017), free public parking(Gu et al., 2019; Kim et al., 2019), free of charge parking (Danielis et al., 2020), approach to on-street parking policy

(Guerra & Daziano, 2020), parking spots increased (Liao et al., 2020), free parking time related to minimum 3 hours (Rotaris et al., 2020). Most of the parking policies have a positive effect on the probability of purchasing EVs, conversely, Liao et al. (2018) found that free public parking cannot have any significant influence on the choice of EVs adoption in their groups, and free parking only during non-peak hours shows no significant effect (Gu & Feng, 2020).

For the aspect of policies reducing general costs, *free lane access and free license plates* are frequently mentioned in the studies. Sheldon et al. (2017) found policies for supporting free single-occupant high-occupancy vehicle (HOV) lane access could increase the probability of purchasing PHEVs, while it was not significant for the entire class group in the research by Abotalebi et al. (2019). As to the free license plate, which are special incentives appeared in China, it is shown that easily obtaining a license plate for an EV has a strong effect on the uptake of EVs (Liao et al., 2019, 2020; Nie et al., 2018; Qian et al., 2019; X. Yang et al., 2017), the willingness to pay for obtaining a free vehicle license for EVs could reach a highest bid price of 106,144 RMB on average (Qian et al., 2019).

2.4.4. **Individual-related variables**

Individual-related variables performed on socioeconomic characteristics are often included in analysis of choice studies. The effects of socioeconomic factors such as gender, age, education level, and household income are different in the various studies. For example, age and gender were found to have significant effects on the utility of EVs in the Cartenì et al. (2016) research, while they were not as significant in the Danielis et al. (2020) and Rotaris et al. (2020) studies. Some researches focused on the stated preference of young group who was expected to buy EVs in the future market. Hackbarth and Madlener (2013) investageted that younger and well-educated group was the most receptive group for the adoption of EVs. Morover, Barth, Jugert, and Fritsche (2016) concerned on young individuals who were more sensitive to the capabilities of high-tech innovation and confirmed the significant role of people’s perceptions and collective. This is also explored by Liao et al. (2019), who have evaluated the influence of attitudes and choices on preferences in busbusiness model, and confirmed yougers have the highest preference for purchasing and leasing BEVs and PHEVs.

Focusing on the student segment, recent research carried out in Italian market was conducted by Miceli and Viola (2017), they identified the significant effect of electrical load in university recharge area for EVs. Experience with EVs, gender distribution, and operating and infrastructural characteristics of the service could lead to widespread acceptance of EVs (Campisi, Ignaccolo, Tesoriere, Inturri, & Torrisi, 2020). The behavior and attitude of users were also regarded as important factors in the adoption of EVs. Carrese S., Giacchetti T., and Nigro M. (2017) conducted a survey on university-based electric vehicle car sharing systems, confirmed the green attitude as the most relevant attribute to effect EVs selection.

The early relevant research on student group in Chinese market was carried out by Zhu, Zhu, Lu, He, and Xia (2012), which was focused on Chinese college students, and confirmed the dominate role of psychosocial (symbolic or affective) values in students' groups. Jeon et al. (2012) conducted a comparison survey to compare the difference of purchase intention of students between Korean and China. S. Yang, Cheng, Li, and Wang (2019) performed a study only with students as respondents and discovered that product cognition on EVs and incentive policies may influence the adoption of EVs among students. X. Zhang, Bai, and Shang (2018) selected master in business administration (MBA) students as their survey respondents to explore perceptions and motivation impact on consumers' adoption. However, Students were less selected as respondent to be analysed in preference studies, as they were usually regarded as insincere, uninterested in filling out data, and unaware of new technology products (Singh, Singh, & Vaibhav, 2020). The studies were sumarized in Table 4.

We have summarized the individual-related variables into two categories: socio-economic characteristics and psychological factors, which were confirmed to affect consumers' heterogeneous tastes. Table 5 has summarized all the socio-economic variables. *Socio-economic characteristics* are the most researched individual-related variables in preference studies. They have performed diverse effects on the utility of EVs. For example, age and gender for Italians significantly affect the utility of EVs in the research by Cartenì et al. (2016) research, while gender and age were excluded as they were not significant in the utility researches in Italian car market (Danielis et al., 2020; Rotaris et al., 2020). Although some of these factors, such as gender, age, income, education, are sensitive to their modeling choice, there is no consistency evidence to confirm positive or negative effects for all socio-economic variables in these researches. *Psychological factors*, which include a set of motivation, perception, learning, attitudes and beliefs, are defined to describe the psychology of individuals that can drive their actions to seek satisfaction. The theory of psychological factors is based on the planned behavior theory (Ajzen, 1991), which emphasizes the behavior intentions shaped by attitudes, subjective norms, and perceived behavioral control. Huijts, Molin, and Steg (2012) built a comprehensive framework of main factors that influence technology acceptance. They explained in detail the influence of attitude, social norms, perceived behavioral control, and personal norm on new sustainable energy technologies. More recently, Cherchi (2017) has investigated the vehicle attributes, environment concerns, social conformity, and parking policies on the preference of EVs and confirmed that the significant effect of social conformity can compensate low driving range and high purchase price on EVs. Rotaris et al. (2020) and Giansoldati, Rotaris, et al. (2020) have considered the car knowledge of respondents and environment awareness in the Italian electric car market. In addition, several other roles of psychological factors on the uptake of EVs were identified in some studies, including subjective norms (L. Li, Wang, & Wang, 2020), environmental awareness (Rotaris et al., 2020), knowledge of electric cars (Giansoldati, Rotaris, et al., 2020), lifestyle compatibility, and symbolic-affective attitudes (Haustein et al., 2021).

However, some researchers have proposed opposite findings on the promotive roles of psychological factors. L. Li et al. (2022) explored the significant role of personal carbon trading (PCT) and tradable driving credit (TDC) in the Chinese market and found that PCT and TDC can influence consumers' choice through economic incentives rather than through psychological motivations. Orlov and Kallbekken (2019) found no significant effect of environmental concerns among their respondents; similar findings were also confirmed in the research of Figenbaum (2020), which showed a neutral attitude on environmental effect for their Norwegian respondents. Sovacool, Abrahamse, Zhang, and Ren (2019) found that knowledge of cars was not significantly associated with the willingness to buy BEVs, while actual driving experience has a significant impact on user choices.

To summarize, the effects of different factors on the adoption of EVs in various research studies might be different. Thus, considering the relationship between psychological factors and the utility of EVs is more likely shown as a country-specific characteristic, researchers are more likely to introduce it as an incorporated part in their choice modeling framework. To be credible, when researchers introduce psychological factors into their choice experiments, they should avoid the overlap with factors that are already performed in choice experiment and pay close attention to the correlation between psychological constructs (Liao et al., 2017).

Table 4 Results concerning on young people

Authors	Sample	Variables	Methodology	Main findings
Hackbarth and Madlener (2013)	German (N=711)	Age, Enviornmental awareness, Education level, Parking lot with charging	MNL, MXL	• Youngers were more likely to choose EVs • Pepole who have enviornmental awareness have high utility on AFV • Pepole with high education level would be likely to choose BEVs or PHEVs • Drivers of small cars with access to parking lot equipped with a socket have high utility on AFVs
Barth et al. (2016)	German (N=601), univerisity student(N=261) and employed (N=386)	Social norms, Collective efficacy	Hierarchical regression analysis (HRA)	• Norms and collective efficacy had stronger effects on acceptance of EVs than cost-related factors
Miceli and Viola (2017)	Italian university student (N=960)	Electrical load, Power plant topology, Energy cost	Markov model	• Electrical load cause demand peak • Directional PV system and photovoltaic sources can prompt charging by users
Campisi, Ignaccolo, Tesoriere, Inturri, & Torrisi, 2020	Italian university student	Socio-demographic (gender), Operating and infrastructural service	Quantitative analysis	• Pepole with experience in using EV have higher acceptance • Gender distribution and service on operating and infrastructural can influnce demand
Carrese S. et al. (2017)	Italian university student (N=950)	Socio-economics, Mobility, Car sharing device attitude, Green Attitude, Sharing Attitude	MNL	• Car sharing device attitude and Green Attitude have a high effect on the utility of EVs • Family income can effect the purchasing power
Zhu et al. (2012)	Chinese university student (N=973)	Demographics, Perceived instrumental and psychosocial values (beliefs of car ownership)	Planned behavior theory	• Car’s image is important for promotion • Social environment of school variable

Jeon et al. (2012)	China and Korea university students(N = 104)	Images, Social norm, Perceived risk of finance and psychology	Partial Least Squares (PLS)	• Social influnce was significant role on the uptake of EVs
S. Yang et al. (2019)	Chinese university students and employees (N = 213)	Product cognitions, Incentive policies, Socio-demographic	Bidirectional stepwise method	• Product cognition could promote the uptake of EVs • Information and subsidy policy have significant roles
X. Zhang et al. (2018)	Chinese university students (N=264)	Demographic, Perceived economic and environmental benefits, Perceived risk, Attitude, Subjective norms and purchase behavior	Structural equation modeling	• Perceived economic, environmental benefits and perceived risks were significant • Promotion attitudes have a great effect on purchase intention • Regulatory focus has significant effect on subjective norm

2.4.5. **Other variables in studies**

There are also some other variables not typically but have been presented in a few studies. The individuals' preferences are found to relate with *vehicle types or size* (Ferguson et al., 2018; Liao et al., 2018). Cirillo et al. (2017) found potential buyers who were willing to pay higher prices on large-sized EVs. Higgins et al. (2017) found younger and high education groups were more likely to choose PHEVs and BEVs.

Environmental performance, defined as carbon emissions, has been seen as a significant factor in stated choice experiments (Jensen et al., 2017). Younger individuals with high environmental awareness are more likely to choose AFVs (Hackbarth & Madlener, 2016). Therefore, government subsidies on carbon emission reduction would encourge the adoption on EVs (Beck et al., 2017). *Experience accompanied with knowledge of EVs*, is expected to have a significant effect on individuals' preferences. According to Jensen et al. (2017), customers often require more time and experience to learn about new products, with increased real-world experience, buyers were more likely to change their initial preference. *Distance to the next charging point*, was proposed as an indicator for calculating the amount of money or time which customers could save when incentive policy was implemented. Rudolph (2016) discovered that establishing a short charging distance between departure and destination promoted the adoption of EVs. This is also consistent with Wang et al. (2021), who confirmed the necessity to improve infrastructure for pedestrians.

Moreover, *Brand design* is the only product attribute researched by Y. Huang and Qian (2018). They have divided the brands into four different levels, and found Chinese brands are considerably less preferred, while respondents are more willing to pay more than 16,000 yuan (approximately $ 2,400) to buy a European brand vehicle than a Chinese brand. *Maximum speed,* compared with conventional vehicles, is regarded as driving performance-impacted factor on the customers' willingness to pay (Jensen et al., 2017). Nie et al. (2018) have used the maximum speed as a vehicle attribute, and found maximum speed has a positive effect to buy an EV. *Payment options and depreciation* (such as hire purchase, personal contract purchase) have been specially researched by Gomez Vilchez et al. (2019), they researched the payment choice changing options and depreciation among six European countries (France, Germany, Italy, Poland, Spain, UK), confirmed respondents were sensitive on the depreciation of the retained value of cars after three years.

2.5. **Conclusions**

We have conducted the literature review to identify the methodology of preference data and the impact of attributes on the utility of EVs. Most of the studies used the stated preference data because of limited ownership number of

EVs market. The widely applied methodology on stated preference studies is described as a discrete choice analysis, focused on estimating the taste parameters to pursue maximum utility. The most basic model is the multinomial logit model (MNL), assuming that error term is i.i.d. and has an extreme value type 1 distribution. Some studies have used a nested logit model to relax the restrictions of irrelevant alternatives (IIA) by clustering alternatives into several nests. Taste parameters in both MNL and nested logit models are fixed, heterogeneity preference is not existing across consumers. In order to capture the preferences, some studies used the mixed logit model (MXL) as a common practice by assuming random distribution of taste parameters (McFadden & Train, 2000). Three methods are used to identify heterogeneity preference: added interaction items between attributes and measured individual specific variables into utility functions, identified latent variables by using a hybrid mixed logit model, and an estimated latent class model (Liao et al., 2019). However, uncertainty factors might neglect important variables which can affect the preference in choice experiments: this would easily cause unreliable prediction of models.

The reviewed studies on stated preference have identified the effect of attributes on the utility of EVs, including financial, non-financial, policy incentives and individual-related variables. We have found that purchase price is the most important mentioned monetary attribute in all of the reviewed studies, which has a significant negative influence on the uptake of EVs. The following cost attributes, including operation cost, ownership cost, travel related costs, or battery lease cost, also have shown highly significant effects on the uptake of EVs. As for the non-financial attributes, including usability-related attribute, infrastructures, technical performance attributes and social conformity, also have shown significant effects on EVs uptake. Specifically, driving range, identified as the major non-monetary attribute, has a highly positive effect on the utility of EVs, which demonstrated the importance of charging infrastructures in promoting the uptake of EVs.

As to the impact of policy attributes, we have categorized them as either financial incentives (price subsidies, cost reduction, tax reliefs or exemptions) or non-financial incentives (fast charging infrastructures, free parking policies, free lane access and free license plates). Governments have implemented incentives to support the uptake of EVs, but there are some mixed findings on the aspect of their effectiveness. Cost reduction is most likely effective on the financial promotion of EVs. Attributes related to charging infrastructures are also significant on the utility of EVs; although some early findings confirmed the significant effect of charging infrastructure related to rates of EV uptake, the direction of causality effects still is an open question. Moreover, the free license plate policy is the special incentive that is most mentioned in Chinese studies; most of the studies have confirmed strongly positive effects on Chinese consumers' preference. All the preferences for the attributes are mostly heterogeneous and commonly accounted for individual-specific variables interaction.

The findings regarding individual-specific characteristics have shown mixed effects on the purchase of EVs, such as gender, age and income. Only psychological factors show stable effects on the utility of EVs, if they are included in studies. Some of the researches explored the social influence and network effects with EVs; they have confirmed the important effects of social networks. This can provide some guidelines for the promotion of EVs, as customers sometimes are misinformed on this new technological product. However, there are no consistent conclusions on all of the individual-specific characteristics.

Moreover, as the reviewed studies are mostly focused on stated preference data, we cannot get information from actual market regarding some unique attributes of EVs. This might easily cause hypothetical bias between stated choices and real behavior patterns in the actual market (Beck, Fifer, & Rose, 2016). Therefore, we will carry out a survey based on real market data in the next chapters, and choose the most important and stable attributes concerning BEVs: purchase price and driving range, to test the roles of them in the Italian and Chinese markets.

Table 5 Overview studies on attributes level

Author(s) (year)	Monetary attibutes	Non-monetary attibutes	Policy attributes	Individual-related attributes	Main finding
Bailey and Axsen (2015)	Purchase price, fuel cost, electricity cost	Home charging: Utility controlled charging(UCC)	Cost incentives	Socio-demographic: more biosphere, younger, more high educated	All sample on cost incentives is more sensitive than renewable incentives
Cartenì et al. (2016)	Travel cost	Travel time	Cost reduction: car-pooling strategies	Socio-economic: male, younger	Travel cost and travel time is significant, electric carsharing service is greater than a traditional one.
Hackbarth and Madlener (2016)	Operation cost and refuel cost, mobility costs, purchase price	Driving range, recharge time	Price subsidies, fuel cost reductions, and tax exemptions, fast charging infrastructure density, environment awareness	Socio-demographic: younger, more environmentally aware, less educated buyers of smaller/cheaper cars, high daily mileage and technical interest on AFVs, elderly and technophile buyers of larger cars on PHEVs	Limited driving range is the major barrier, battery research and fast-charging network can increase preference, “AFV aficionados” have the highest willing to pay for the improvement of all vehicle attributes, tax exemptions and non-monetary incentives are more cost effective.
Y. Yang et al. (2016)	Purchase price, charging cost, travel cost	Charging station, cruising (driving) range, charging time , energy consumption	Fast charging infrastructure	Socio-economic: female, educated, low income	Initial state of charge (SOC) at origin of BEV is the most important factor, drivers are preferred to choose routes with charging station closer to origin, charging route choice is sensitive on charging time and distance from origin to charging station.
Beck et al. (2017)	Purchase price,operation cost	Driving range, recharging time, vehicle emissions	Non-financial incentives: emission reduction	Socio-demographic: not analysed	Environmental concerns is significantly influence, more cared on home battery technology.

Cherchi (2017)	Purchase price, parking cost	Driving range	Parking price, parking spaces reserved for EV	Psychological: socialconformity, injunctive norms	Social conformity effects and informational conformity are highly significant, injunctive norms and social-signaling plays important roles, combined parking policies (parking price and slots reserved for EV) can be effective.
Cirillo et al. (2017)	Purchase price, fuel price, fuel economy	Recharging range, vehicle size	Economic incentives: moderate prices	Socio-economic: younger, male with high education	Consumers prefer newer vehicles with larger size, higher fuel economy, lower purchasing price, and lower fuel price, price sensitive (include electricity price), younger people are more like BEV, preference only changed on long term periods.
Higgins et al. (2017)	Purchase price, maintenance cost, fuel cost	Vehicle body size or type, electric and gasoline range, battery warranty, charging station, home and public charging time	Cash intensive, public charging station, high-occupancy vehicle (HOV) lane access	Socio-economic: age, education, and the importance of fuel economy and reduced or eliminated emissions	Younger and high educated prefer PHEVs and BEVs, education had no effect in full-sedan and luxury categories, customers on economy body types, SUV and minivan segments show low interest on PHEVs and BEVs, psychological factor plays a role on preference, cash incentive: vehicle cost incentive is more important.
Jensen et al. (2017)	Purchase price, fuel or electricity costs,	Driving range, Environmental performance: carbon dioxide emissions,	Registration tax exemption, free parking, free charging, lane	No estimate	The effect of diffusion can increase more penetration of EVs, the market share in Norway has been strongly

		driving performance: top speed, charging options, battery lifetime	access		influenced by incentives, real-life experience is very important.
Rudolph (2016)	Purchase price, fuel/charging costs	Charging infrastructure	Direct purchasing grant, vehicle tax reduction, emission based parking costs, fuel taxation and availability of charging infrastructure	Socio-demographic and socio-economic: the year mileage up to 15,000 km, annual transit pass holders for PT, people using a bicycle	All subsidies can increase attractive , people have mobility patterns with low energy ratio are more like to choose, increased car number should accommodate with parking facilities.
Sheldon et al. (2017)	Purchase price, refuel cost,	Driving range, charging station density	High-occupancy vehicle (HOV) access, federal income tax incentive	Socio-demographic and socio-economic: income, early adopter, pro environment, use gas mode daily, commute under 20miles, parking at work	Financial incentives stimulate fewer BEV purchase, willingness to pay for customers on range up to 300miles and $900 for free single-occupant HOV lane access, charge at home is more important for BEV, less urban respondents do not like all PEVs, and PHEV purchasers would not purchase BEV.
Smith et al. (2017)	Purchase price, running costs	Driving range, charging infrastructure, charge time, emissions, noise level, battery capacity, engine size, environmental concerns excitement for learning new technologies, perceived usefulness, subjective norms	No policy attibutes	Socio-demographics: income, vehicles/household, age, education	non-traders (Best) more cared on Environmental concerns and Subjective norms, more likely to choose EV, attitude play an important role on social norms, adopters are more likely younger, more educated and male, socio-demographics is not a key variable
X. Yang et al. (2017)	Bid price for obtain a license plate,	Wait time, driving range, environment	Subsidy	Socio-economic: younger, low income, household with more	"Easy to obtain an electric car license plate" and

		friendly		members and stable income	“Subsidy” are important as technological advancement, buyers in Shanghai more prefer license plate auction, household with more members and stable income more likely to EV, The gender and education level do not affect policy preference.
D. Yang and Timmermans (2017)	Energy price, travel cost, operation cost, capital price,	Benefit to environment, travel distance reduction,	Public transit policy, Fuel price policy, Fuel emission policy	Socio-demographic: income, age, household with members, travel allowance	Fuel price policy is effective, cost-related characteristics and choice option availability influence choice, older, low income and with children than 12years more likely EV.
Ferguson et al. (2018)	Purchase price, maintain cost	electric/gasoline range, Public charging station availability, public charging time, home/work charging, vehicle body type	Cash incentive, Free municipal parking, Battery warranty, HOV access, No tolls	Socio-demographic: income, age, gender, social pragmatism with risk aversion, geography	Attitudes and beliefs, environment concerns, general attitudes about technology, are sensitive, younger, urban and daily travel circumstance people more like BEV, for economic vehicle type are more preferred, driving range, purchase price, maintenance cost are sensitive
Hahn et al. (2018)	Purchase price, operation cost	Fuel stations availability	Purchase price reduction, fuel availability increase, driving range increase.	Socio-demographic: car ownership, low income, male, small family, information of green vehicles, inclusive value oil-consuming nest	vehicle attributes and socio-demographic variables have different effects for different sizes of vehicles, reduction in purchase price, fuel availability increased was more effective.

Y. Huang and Qian (2018)	Purchase price, annual operation cost	Driving range, brand design, emission level, product design	Availability of fuel/charging station, Capability of home charging, purchase subsidy, vehicle license, driving restriction, congestion charge, access to bus lane	Psychological: moral norm, word-of-mouth, risk aversion	Chinese consumers in lower-tier cities are sensitive to monetary attributes, service attributes, moral norm and risk aversion are important.
Liao et al. (2018)	Purchase price, energy cost,	Driving range, electric range, fast charging density, fast charging duration	Road tax exemption, free public parking	Socio-demographics: mobility guarantee(week), younger and more frequent public transport users	The probability of being a member of EV buyers decreases with age, public transport and car commuting frequency, battery leasing is important
Liu and Cirillo (2018)	Fuel price, purchase price	Driving range,fuel economy,	Environmental incentive	Socio-demographic: age, education, gender, vehicle size, owned vehicle number, job	Dynamic models have a better performance on predicting vehicle market share, consumers are more interested on gasoline and hybrid cars, EVs market highly rely on electricity price, purchase price, MPG equivalent electricity and recharging range.
Nie et al. (2018)	Fuel cost, Purchase price	Driving range, charge time, maximum speed, emissions	Purchase subsidy	Socio-demographic: gender, age, education, income, job, car owned number, awareness	Consumers prefer longer driving ranges, but no more than 400km, fast charging technology is necessary to be improved, subsidies on reducing charge time, lower pollution, increase maximum speed, improve charging infrastructure in urban and rural area including on the expressway.

Wolbertus and Gerzon (2018)	Purchase price, Charging points time-based fee,	Time, Lease, Currently moving	On street parking, free charging facilities	Socio-demographic : gender, age, annual income, type of EV, car ownership, private charging point	Time-based fee on the decision to remove an EV from a charging station influence choice, heterogeneity between respondents are more influenced the policy makers.
Abotalebi et al. (2019)	Purchase price, maintenance cost, fueling/charging cost	Charging stations, public charging time, battery/ gasoline range, emission, battery warranty, charging time	Cash incentive: price subsidy, Non-cash incentive: HOV lane access, Free parking, Free toll roads	Socio-economic and demographic: age, gender, education, car ownership, keeping vehicle time, homeowner, vehicle economy size, live location	High purchase price, limited charging stations, and long charging time either at home or at public stations are negative,
Gu et al. (2019)	Purchase price, maintenance costs, operating costs	Driving range, access time, vehicle availability, travel time to charging station, charging time	Free parking, Bike lane availability	Socio-economic: gender, education, income	Driving range and purchase price are sensitive factor, people who have a job prefer an electric car, free parking policy has a positive effect, but only on non-peaking hours is no significant effect.
Gomez Vilchez et al. (2019)	Purchase price, operating costs, payment options and depreciation (Hire purchase, Personal contract purchase)	Driving range, refueling time, emissions	Purchase subsidy, ceiling on the value added tax	Socio-economic: age, education	Purchase price and government financial interventions are the crucial factors, respondents are cared depreciation on the retained value of car after three years.
Kim et al. (2019)	Purchase price	Charging infrastructure, driving range	Public parking, purchase subsidy, tax exemption, highway lane access	Socio-demographic: age, gender, education, BEV experience and knowledge, perception on incentives	Experiences with BEVs and government policies are key promotion factors. Education and age are positive factor, high vehicle price, poor charging infrastructure, and vehicles performance are not significant.

Kormos et al. (2019)	Purchase price, fuel cost	Driving range, recharge/refuel time, Destination recharging, Highway-based fast recharging, refueling access	Purchase sussidies	Socio-demographic: region of residence, lifestyle, biosphere value, age, income, education, dwelling type, household	The preference of BEV and HFCV are same, PHEVs are preferred about three times over them, The ZEV driving range, work charging or destination charging are insignificant, PEV-enthusiasts has a highly preference on PHEVs and BEVs.
Liao et al. (2019)	Purchase price, Energy cost	Driving range, Fast charging duration, Fast charging availability	Road tax exemption, Free public parking, Mobility guarantee	Socio-demographics: gender, age, household number, education, monthly income	Vehicle leasing is the most preferred than full price purchase, Mobility guarantee for up to 2 weeks per year is insignificant, Younger, lower income, high educated, students, more car ownership are positive effect.
Ma, Fan, et al. (2019)	Purchase price	Charge time, driving range, battery capacity	No list	No special analyze	Charging time is more important, Compact and small BEVs, fast charging batteries and short charging time are more preferred.
Pan et al. (2019)	Charging price, parking price,	Initial state of charge (SOC), distance to the next destination, excess range,	Charger utilization	Socio-demographics: male, income, purchased EV in past year	SOC, charging price, parking price, and excess range have negative effect on charging utility, Respondents purchased EV in past year is significantly less likely to charge, Lower education, female, or purchased EVs more than a year are more likely to be risk averse.
Qian et al. (2019)	Purchase price, Annual running cost	Driving range, Coverage, speed, permission and	Government subsidy, Free vehicle licensing	Socio-economic: age, gender, annual income, family size	Home charging is the most significant effect, Free license immediately has

		charging speed of public charging stations			greater effect than 10,000 yuan government subsidy
Ashkrof et al. (2020)	Travel cost,	Travel time, fast charging, charging time, waiting time, original battery power,	Fast charging infrastructure	Socio-demographic: female, older, higher income	Travel time and travel cost have a negative effect on route alternatives utility, People don't like to stop for recharging car during commuting trip, Initial state of charge (SOC) is crucial to select a route.
Danielis et al. (2020)	Purchase price, fuel economy	Driving range(EV and petrol cars), distance between charging stations, Vehicle brand, Fast charging time	Free charge parking	Socio-economic: age, education, family members with license, owned garage, annual trip distance, EV knowledge, driving experience, environment concern and association.	Short annual distance is less competitive, small to medium car of EVs is expensive and limited, Purchase price, fuel economy, and driving range, time spent to fast charge, free of charge parking are significant, WTP for a 1-km increase in the driving range is lower
Ghasri et al. (2019)	Purchase price, set up cost, operating costs	Recharge time	Supporting scheme: Rebate on upfront cost, Energy bill discount until 2025	Socio-demographic: age, education, employment, household structure, vehicle ownership, income, accommodation	Vehicle ownership negatively effect, Education and employment levels have positive affect, Design, environment, safety interacted with purchase price are sensitive.
Gong et al. (2020)	Purchase price, cost per km	Recharge time, Range in a single recharge	Access to bus lane, Rebates on upfront costs, Rebates on parking fees until 2025, Energy bill discount until 2025, Stamp duty discount until 2025	Socio-demographics: household type, age, total income, education, gender, employment, dwelling ownership	Energy bill discount until 2025 and Rebates on the upfront cost were most preferred, Access to bus lane incentive was the only significantly non-financial incentive.

Guerra and Daziano (2020)	Purchase price, driving cost, EV parking price	Driving range, charge time, location of parking, time to find space	On-street parking permits	Socio-demographic: gender, education, income, age, race/ethnicity, house type	Parking and charging stations, on-street parking, technology are important factors, Group of conservative, married, and wealthy are more cared on range and charge time, but less on parking.
Gu and Feng (2020)	Purchase price, maintenance costs, operating costs	Driving range, access time, vehicle availability, charging opportunity, average travel time to charging station, fast charging time	Free parking	Socio-demographic: gender, income, house size, house ownership, house type	Low income people, users owned home energy equipment are more like EV.
Ten Have et al. (2020)	Price	Charging point availability, frequency of using fast charging, route	Not list	Socio-demographic: gender, income, education, access to private parking, driving feeling, important of travel time	Fast charging is important factor on choice, Satisfaction levels, travel behavior and vehicle characteristics are insignificant.
Jin et al. (2020)	Cost	Remaining range, Access distance, Egress distance, Vehicle model, Discount, Walking distance for public transport, In-vehicle time, trip purpose, trip distance	Not list	Socio-demographic: gender, age, income, education, occupation, BEV number, trip frequency, main transport mode on weekdays, BEV sharing experience	Access distance, egress distance, remaining range, and vehicle model are significant effect, BEV sharing can serve as substitute in long distance trip, Travelers are more cared on longer remaining range more than access distance.
Liao et al. (2020)	Purchase cost, maintenance costs, operating costs	Access time to shared car, Fuel type, Car availability, Return location	Not list	Socio-demographic: age, gender, education, income, household, occupation, car bought choice, new purchased plan, frequency of commuting trip by car/public transport/bike, symbolic/environmental/hedonic	40% of car drivers accept car sharing trips, Higher trip replacement cannot reduce car ownership, Changed System attributes cannot influence car sharing decision.

				attitude	
Lu et al. (2020)	Purchase price	Charging convenience, cruising range,	Driving restriction, License plate restriction, Purchase tax, Purchase subsidy, Vehicle use subsidy, Bus line driving permit	Socio-demographic: age, education, income, vehicle ownership, purchase demand, purchase budget, daily travel distance	Purchase subsidy policy has a significant influence, Vehicle use subsidy has to be set at $714 to maintain original BEV choice probability.
de Luca et al. (2020)	Price, Monthly change cost between EV and conventional car	Technical features, emission, design, consumption, fuel range, charging	Not list	Socio-demographic: age, gender, household, car ownership, car type, trip kind	Psychological factors play an important role on the choice
Miele et al. (2020)	Purchase price, Fuel cost	Driving range, home/work place/ public charging, fast charging, station availability, vehicle type	Universal/ Ambitious infrastructure	Socio-demographic: familiar degree of ZEV knowledge	Infrastructure provision is not significantly effect, Policy promotion should be stimulated to increase ZEV.
Tchetchik et al. (2020)	Price	Maximum speed, Driving range, Charging/fuel time, Accessories standard, Number of people who drive the car	Policy tool: subsidies, tax breaks	Socio-demographic: age, gender, income, education, household size	The competing technologies of HEVs and BEVs will co-exist, Government promotion on HEVs might cause BEVs are promoted increased, Hedonism and environment should be combined into HEVs.
Zhou et al. (2020)	Total cost to recharge,	Charge time, Distance to charge station, Remaining battery, Maximum battery energy	Not list	Not list	The minimum of 200km and 300km for taxi and private cars separately can get the need for driving, Time available for recharge, distance to nearest charging station, and total recharge cost are significant signs.

Rotaris et al. (2020)	Purchase price. Fuel economy	Driving range, max distance between fast charging stations, Fast charging time, car type (middle and small), environment awareness, EV experience	Free parking	Socio-economic: country, gender, income, age, experience on EV	Italian are purchase price sensitive and Slovenians are driving range sensitive, policy on free parking is significant, Female has a higher environment sensitivity, while male has BEV knowledge sensitive.
Wang et al. (2021)	Charging fee	Queuing time, Excess range, Parking time, Satisfaction, Battery state of charge (SOC)	No list	Socio-demographic: gender, income, driving experience. Age, risk aversion,	With cost increased, no charging was preferred, Vehicle state, destination state and charging facilities are significant are on charging behavior, SOC, excess range and parking time, satisfaction of charging facilities are key factors, Risk averse and rich experienced drivers prefer to charge.

3. Modeling Framework

3.1. **Introduction**

Revealed and Stated preference data are commonly used in discrete choice models. Revealed preference (RP) data is used to describe the real choice of agents in the actual market. Stated preference (SP) data is used to collect possible choices and preferences of respondents by presenting hypothetical scenarios. These two kinds of data are complementary and can be used to better correct bias, to identify effects of attributes and to improve efficiency of parameter estimation based on the assumption of common effects. This chapter describes the three most widely used discrete choice methodology: the multinomial logit model (MNL), mixed logit model (MXL) and hybrid mixed logit model (HMXL). All individuals in our studies are assumed to be pursuing utility maximization. We start our analysis of the models by discussing the most basic widely used model: the multinomial logit model (MNL) (section 3.2). In order to relax the restriction of independence from irrelevant alternatives (IIA), we have used a mixed logit model (MXL), which allows for random taste variations of individuals, unrestricted substitution patterns, and correlation of non-observed factors over time or individuals (section 3.3). Then, considering the proposed statement for each individual, we have used the hybrid mixed logit model to assess the latent information (section 3.4).

3.2. **Multinomial Logit model (MNL)**

The discrete choice model is based on the random utility theory, assuming that decision makers are rational and pursue maximum utility when they face choices among multiple alternatives. The utility function can be composed by three parts: a non-stochastic, a linear parameter part that depends on observed data, a stochastic part that is correlated with alternatives and heteroskedastic where the stochastic part is independent and identically distribution. The parameters of the MNL model are fixed and the error term is assumed to be independent and identically distributed (IID) with an extreme value type I distribution. Then the utility function for individual q from alternatives j can be written as follows:

$$\mathbf{U_{qj} = \beta x_{qj} + \mu_{qj} + \varepsilon_{qj}} \qquad 1$$

Where x_{qj} is a vector of observed variables related to individual q and alternatives j. β is a parameter that characterizes the choices from the overall population. μ_{qj} is a random item, whose distribution depends on parameters and observed data related to individuals and alternatives. ε_{qj} is a random term with independent and identical distribution (IID) which does not depend on parameters and observed data.

When ε_{qj} has an extreme value type I distribution, the unobserved component μ_{qj} is independent of alternatives and its value is zero, then the utility function becomes:

$$\mathbf{U_{qj} = \beta x_{qj} + \varepsilon_{qj}} \qquad 2$$

Here, the error item ε_{qj} follows a Gumbel distribution where each ε_{qj} is independently, identically distributed extreme value, then the standard logit model becomes a multinomial logit model (MNL). Assuming ε_{qj} is a normalized distribution with zero mean and standard covariance, then the density ε_{qj} is denoted as $f(\varepsilon_{qj})$

$$\mathbf{f(\varepsilon_{qj}) = exp(\beta x_{qj}) / \textstyle\sum_j exp(\beta x_{qj})} \qquad 3$$

Defining V_j as the systematic part of utility function, not including the error term, $V_j = \beta x_{qj}$, then the choice probability of MNL model can be simply expressed as:

$$\mathbf{P_{qj} = \frac{exp(V_i)}{\sum_{j=1}^{J} exp(V_j)}; j = 1, \ldots, i, \ldots, J \;\; i \neq j} \qquad 4$$

The probability that an individual chooses alternative i from all alternative set J is equal to the ratio of the observed utility index of alternative i to the sum of observed utility index of all alternatives J, including the i-th alternative.

Specifically, in our sample, we have assumed that an individual *q* can select alternative *j* from a set of *J* alternatives, the utility function is expressed as follows:

$$\mathbf{U_{qj}^{c} = ASC_{qj}^{c} + \textstyle\sum_k \beta_{kj}^{c} X_{kj}^{c} + \sum_r \emptyset_{rkj}^{c} SE_{rq}^{c} + \varepsilon_{qj}^{c}} \qquad \mathbf{5}$$

where *c* indicates the two countries (Italy and China); *j* is the proposed powertrain alternative (petrol, diesel, LPG, CNG, BEV, HEV, or PHEV); ASC_{qij}^{C} is the alternative specific constant of individuals *q* with the proposed alternatives *j* in each country *c,* which is used to capture the effects of all attributes that were not included in the choice experiments; X_{kj}^{c} is the *k* alternatives' specific attributes (i.e., purchase price (net) and driving range); β_{kj}^{c} is the vector of coefficients; SE_{rq}^{c} is the socioeconomic characteristic *r* of the respondents *q* in each country *c*; $\emptyset_{r}^{c}$ is the vector of the corresponding coefficients; and ε_{qj}^{c} the error item that is with independent and irrelevant distribution (i.i.d.).

However, the MNL model imposes three limitations on extreme value distribution: random taste variation, unrestricted substitution patterns, and correlation in unobserved factors over time (Train, 2009).

3.3. Mixed logit model

The mixed logit model (MXL) is a highly flexible model on the choice model or distribution of preferences based on random utilities. It overcomes the three limitations of standard logit model, relaxing the assumption of independence from irrelevant alternatives (IIA) by allowing for random taste variations among individuals and unrestricted substitution patterns between alternatives. Any choice model with any distribution of preferences can achieve any degree of accuracy by using mixed logit model (McFadden & Train, 2000). Several behavioral conditions are formulated in the MXL model: (a) flexible substitution patterns, (b) scale difference in stated preference choice contexts, (c) heterogeneity preference existing across individuals for alternatives. The most widely used form is based on random coefficients, and the function can be written as

$$\mathbf{U_{nj} = \beta' x_{nj} + \varepsilon_{nj}} \quad 6$$

The coefficient β' is varied over individuals with the density $f(\beta|\theta)$. The density is a function of parameters θ with mean and covariance of given β. This specification is the same as for the standard logit model (MNL) except β varies over individuals rather than being fixed. The individuals have known their own β_n and ε_{nj} and choose alternative i if and only if $U_{ni} > U_{nj} \; \forall \; j \neq i$. Then the conditional probability on β_n is expressed as

$$\mathbf{L_{ni}(\beta_n) = \frac{e^{\beta_n' x_{ni}}}{\sum_j e^{\beta_n' x_{nj}}}} \quad 7$$

However, the researchers cannot give a condition on $\boldsymbol{\beta_n}$ as it is not known, so the unconditional choice probability is expressed as the intergral of $\mathbf{L_{ni}(\beta_n)}$ over all possible variables of $\boldsymbol{\beta_n}$.

$$\mathbf{P_{ni} = \int \frac{e^{\beta_n' x_{ni}}}{\sum_j e^{\beta_n' x_{nj}}} f(\beta|\theta) d\beta} \quad 8$$

Since the probability is not a fixed form, it can be simulated with any given value of β_n. $f(\beta|\theta)$ is specified to be continuous, the values of β_n have interpretable meanings that reflect the tastes of decision makers. Researchers are free to specify the distribution of $f(\beta|\theta)$ that best corresponds to their datasets. Any distribution can be utilized, including the normal, lognormal, uniform, triangular, and gamma.

To capture the customers' stated choices, we used a random parameter to account for the random heterogeneous preference. In our model, the utility of the unobserved factors ε is normally distributed with zero mean and standard variance. Then, we defined the utility U_{jnt}^{c} for each individual *n* with alternative *j* in the choice task *t* for the countries *c* (*c* = Italy or China). The utility functions are written as follows:

$$\mathbf{U_{jnt}^{IT} = ASC_{qj}^{IT} + \sum_k \beta_{kj}^{cIT} X_{kj}^{IT} + \sum_r \emptyset_{rkj}^{IT} SE_{rq}^{IT} + \varepsilon_{qj}^{IT}} \quad \mathbf{9}$$

$$\mathbf{U_{jnt}^{CN} = \lambda(ASC_{qj}^{CN} + \sum_k \beta_{kj}^{CN} X_{kj}^{CN} + \sum_r \emptyset_{rkj}^{CN} SE_{rq}^{CN} + \varepsilon_{qj}^{CN})} \quad 10$$

where X_{kj} is the vector of vehicle attributes, including purchase price and driving range, in our samples; ε_{qj}^{c} denotes the error components and includes the unobserved factors with normal distributions (a zero mean and a standard variance); and $\lambda = \sigma^{CN}/\sigma^{IT}$ is a scale parameter that is set to the ratio of the standard deviations of the error terms ε_{qj}^{c}. It is the inverse of the variance associated with the unobserved variables in the specifications. Since the error terms included unobserved variables that might cause different variances between the two countries, we used λ to describe the relative variance, normalized to 1 for the Italian sample since Italy is assumed to be the reference country in our sample, then we used the variance of Chinese sample compared to the reference one.

Specifically, the coefficients of the two attributes (purchase price and driving range) are expressed a normal distribution with mean μ and standard deviation σ at the inter-individual level. The form is expressed as followed:

$$\boldsymbol{\beta^{c}}_{\mathbf{price}} = \boldsymbol{\mu}_{\boldsymbol{\beta^{c}}_{\mathbf{price}}} + \boldsymbol{\sigma}_{\boldsymbol{\beta^{c}}_{\mathbf{price}}} * \boldsymbol{\varepsilon^{c}}_{\mathbf{price}} \qquad 11$$

$$\boldsymbol{\beta^{c}}_{\mathbf{range}} = \boldsymbol{\mu}_{\boldsymbol{\beta^{c}}_{\mathbf{range}}} + \boldsymbol{\sigma}_{\boldsymbol{\beta^{c}}_{\mathbf{range}}} * \boldsymbol{\varepsilon^{c}}_{\mathbf{range}} \qquad 12$$

Where μ is the estimated mean for β, σ is the standard deviation term in the inter-individual level, multiplying the inter-individual level standard normally distributed ε (error term), to capture inter-individual heterogeneity. It can reflect the deviation of these data sets. When the standard deviation is highly significant, it indicates that these coefficients do indeed vary in respondents. The mean parameter estimation is positive, suggesting values closer to zero; that is, individuals are less sensitive to the parameter compared with the others.

3.4. Hybrid Choice Model framework

In behavioral science, some variables cannot be directly defined and measured; in order to identify the influence variables, latent variable modeling is used for inferring information about latent variables. The hybrid choice model is the main method to account for the heterogeneity. It is integrated in models and methods to extend the traditional discrete choice model and random utility model (RUM). Alternative specific constant (ASC) is used to capture the effect of unobserved variables that are not included in the model, ceteris paribus, to describe the preference for a specific mode in our utility functions.

The utility function is based on the linear assumption, and expressed as:

$$\mathbf{U^{C}_{qij}} = \mathbf{ASC^{C}_{qij}} + \sum_{\mathbf{k}} \boldsymbol{\beta}^{\mathbf{c}}_{\mathbf{kij}} \mathbf{X^{c}_{ki}} + \sum_{\mathbf{r}} \emptyset^{\mathbf{c}}_{\mathbf{rkj}} \mathbf{SE^{c}_{rq}} + \sum_{\mathbf{l}} \boldsymbol{\xi}^{\mathbf{c}}_{\mathbf{r}} \mathbf{LV^{c}_{lq}} + \boldsymbol{\varepsilon}^{\mathbf{c}}_{\mathbf{qij}} \qquad 13$$

Where c indicates the two countries (Italy and China), i is the proposed alternatives (petrol, diesel, LPG, CNG,BEV,HEV,PHEV), j is the database type (RP and SP), q indicates as individuals. $\mathrm{ASC}^{\mathrm{C}}_{\mathrm{qij}}$ is the alternative specific constant of individuals q with proposed alternatives i in the different database j of each country c. $\mathrm{X}^{\mathrm{c}}_{\mathrm{ki}}$ is the k alternative specific attributes (purchase price and driving range), β^{c}_{kij} is the vector of coefficients. $\mathrm{SE}^{\mathrm{c}}_{\mathrm{rq}}$ is the socio-economic characteristic r of respondents q in each coutry c. $\emptyset^{\mathrm{c}}_{\mathrm{r}}$ is the vector of corresponding coefficients. $\varepsilon^{\mathrm{c}}_{\mathrm{qij}}$ is the i.i.d. error term with extreme value type 1 distribution.

$\mathrm{LV}^{\mathrm{c}}_{lq}$ is a latent variable, used to explain the latent attitudes. As the latent variables can not be directly observed, researchers normally use a measurement function to evaluate them. When respondents are asked to use a Likert scale to describe their attitudes within a large amount of categories, the measurement is expressed as a discrete equation:

$$\mathbf{Z_{pcq}} = \begin{cases} \mathbf{1\ if\ (-\infty) < Z^*_{pcq} \leq \gamma_{pc1}} \\ \mathbf{2\ if\ \gamma_{pc1} < Z^*_{pcq} \leq \gamma_{pc2}} \\ \mathbf{3\ if\ \gamma_{pc2} < Z^*_{pcq} \leq \gamma_{pc3}} \\ \cdots \\ \mathbf{w\ \ if\ \gamma_{pc(w-1)} < Z^*_{pcq} \leq \infty} \end{cases} \qquad 14$$

Z_{pcq}(zeta) is the indicator for categorized response, p is the indicator and q is the respondents, Z_{pcq} is defined by a set of threshold estimated parameter τ (tau) and *w* is the discrete choice response of the proposed statements for each indicator p. Then indicator Z_{pcq} is simplified as:

$$\boldsymbol{Z^*_{pcq} = \tau_{lpc} LV_{lcq} + \vartheta_{pcq}} \qquad 15$$

Where l is the latent variables (l=1,…,L, L=4, indicating charge range, economic, environment, driving). ϑ_{pcq} is the error item with the distribution $\vartheta_{pcq} \sim N(0, \sigma^2)$.

Then the structure equation of each latent variable is expressed as a function with socio-economic characteristics and an error item $\boldsymbol{\eta}_{lcq}$ (eta) with normal distribution.

$$\boldsymbol{LV_{lcq} = \textstyle\sum_l^L \gamma_{lcq} Z_{pcq} + \eta_{lcq}} \qquad 16$$

As the databases of RP and SP are different, the variance of error terms may differ in the databases, so we have introduced a scale parameter λ to describe the variance of error term in each database. The scale parameter λ is normalized to one for the Italian sample, and the estimated λ to the variance of the error item in the Chinese sample, then compared to the Italian one.

Finally, we have got our hybrid utility function in our samples. The utility function is with alternative i=(1,…,I) and individual n=(1,…,N) in the choice situation t=(1,…,T), the expression is listed as:

$$\boldsymbol{U^{IT}_{qi} = ASC^{IT}_{qi} + \textstyle\sum_r \alpha^{IT}_{rk} SE^{IT}_{rq} + \sum_k \beta^{IT}_{ki} X^{IT}_{ki} + \sum_l \gamma^{IT}_l LV^{IT}_{lq} + \varepsilon^{IT}_{qi}} \qquad 17$$

$$\boldsymbol{U^{CN}_{qi} = \lambda(ASC^{CN}_{qi} + \textstyle\sum_r \alpha^{CN}_{rk} SE^{CN}_{rq} + \sum_k \beta^{CN}_{ki} X^{CN}_{ki} + \sum_l \gamma^{CN}_l LV^{CN}_{lq} + \varepsilon^{CN}_{qi}}) \qquad 18$$

c: Italy (IT) and China (CN)
i: the proposed alternatives (Petrol, Diesel, LPG, CNG,BEV,HEV,PHEV)
q: respondents in samples
λ: scale parameter (Italy equals to 1)

$\mathrm{ASC}^{\mathrm{C}}_{\mathrm{qi}}$: the alternative specific constant of individual q with proposed alternatives i of each country c

$\mathrm{X}^{\mathrm{c}}_{\mathrm{ki}}$: alternative specific attributes k (purchase price and driving range)

β^{c}_{ki}: vector of coefficients
SE^{c}_{rq}: socio-economic characteristics r of respondents q in each country c
α^{C}_{rk}: coefficient of socio-economic variables
γ(gamma): coefficients of latent variables
LV^{IT}_{lq} ,LV^{CN}_{lq}: latent variables (charging range, economic variable, environment, driving)
ε^{c}_{qij}: error term with extreme value with type 1 distribution

The HMXL consists of three parts: the measurement equation, the structural equation and the parameters in utility functions. For the measurement equation, the parameter (τ) is used to explain the relationship between latent variables and indicators used to describe latent attitudes. The parameter (γ) in the structural equation is used to explain impacts of socio-demographic variables on the underlying structures. The parameter (λ) is to explain the relationship between latent variables and utility functions.

3.5. **Conclusions**

For the modeling framework, we have formulated three different discrete choice methodologies: the multinomial logit (MNL) model, the mixed logit model (MXL), and the hybrid mixed logit model (HMXL). The utility functions in our study are assumed to be linear, composed of alternative specific constants (ASCs), the socio-economic characteristics of all respondents, car-specific attributes with the purchase price and driving range in each choice task and the error term. The basic model is the MNL model, assuming the observed utility is deterministic and the error term is independent and identically distributed (IID) with type I extreme value distribution. The assumption in MNL is restrictive: it does not allow for correlation among choices over time, flexible substitution for alternatives and preference variation. If we set a relaxed restriction on taste variation, choice correlation and flexible substitution patterns, the model is expressed as the MXL model. In MXL, the parameter of attributes of alternatives is varied over decision-makers rather than being fixed. Considering the attitudes, HMXL is used to capture information with latent variables. It consists of three parts: the measurement equation, the structural equation, and the parameters in utility functions. The HMXL enhances the potential capabilities of the predicted choice models.

However, all discrete choice models have identification problems, which require setting specific parameters to a given value in order to estimate the model. They focus on individuals, ignoring the social interaction and impacts among decision-makers. Although these factors can be incorporated into the model structure, this will increase the dimensionality barriers associated with model analysis (Ben-Akiva M., McFadden D., & K., 2002). The other limitation relates to the explanation, As the latent variables can not be directly in hybrid choice model, it is difficult to confirm predictive accuracy, different model structures need to be distinguished.

4. Experiment Design

4.1. **Introduction**

In this chapter, we started our study by providing a comprehensive definition of alternatives and attribute levels. The alternatives include various automobile propulsion systems in both Italy and China, with attribute values derived from actual market data (section 4.2). Then, we described the experiment design, including the definitions of the simulation scenarios of stated choices on different cars (section 4.3).

4.2. **Definition of alternatives and attribute level**

In our survey, we have considered seven propulsion systems in Italy, which are Petrol cars, Diesel cars, Liquefied Petroleum Gas cars (LPG), Compressed Natural Gas cars (CNG), Battery Electric cars (BEVs), Plug-in Hybrid Electric cars (PHEVs), and Hybrid Electric cars (HEVs). However, there are only five options in the Chinese survey as LPG and CNG was excluded. The reason is that CNG is predominantly used in urban taxis and buses, whereas LPG is primarily used in commercial vehicles such as heavy trucks, long-distance buses and engineering vehicles (Kang, Earlay, & An, 2010). Moreover, due to high storage density, insufficient supply, and poor performance in terms of driving range, the share of CNG and LPG in the passenger car market is substantially lower in China.

The attribute selection in our stated-choice experiments was a crucial process. Numerous potential features were explored in previous studies, and their specifications in terms of indicators were heterogeneous in the model application (Coffman et al., 2017; D. Greene, Hossain, Hofmann, Helfand, & Beach, 2018; Liao et al., 2017; Noel et al., 2020). By examining the stated preference studies related to the Italian and Chinese EVs markets, e.g., Danielis et al. (2020), Rotaris et al. (2020), She et al. (2017), and L. Li et al. (2022), we have selected the two important attributes which have strong effects on the car choices: purchase price (net) and driving range. The purchase price is the net price, excluding applicable subsidies and taxes. The driving range is the maximum driving distance for a car running with a full tank or fully charged per time (calculated per km). The choices focusing on only two significant attributes can lessen the confusion of our respondents, thus allowing them to concentrate on the exact choice scenarios for each car segment. The respondents were asked to make their best choice under normal conditions (such as excluding the coronavirus disease 2019 (COVID-19) pandemic). Moreover, we considered the real market with best-selling cars that are currently available in the Italian and Chinese markets, excluding the Chinese Wuling MINI EV model with its limited range. The levels listed in our experiments are referred to the list price from manufacturers after the subsidy. The list levels of driving range are multiplied by fuel tank capacity with the number of kilometers that cars can cover with one liter of fuel. The price level and driving range level in both two countries are reported in Table 6 and Table 7. The actual market distribution with the best-selling car models and brands that are currently available in the Italian and Chinese car markets is listed in Appendix A.

Table 6 Levels of purchase price and driving range on vehicle types in China sample

Vehicle type	Price levels (¥10,000)	Driving range (km)
Petrol	90,110,130,150,170	700,850,1000
Diesel	120,140,160,180,200	800,1000,1300
BEV	90,130,150,200,250	400,500,600
PHEV	130,160,180,220,250	800,1000,1300
HEV	110,130,150,170,200	900,1100,1300

Table 7 Levels of purchase price and driving range on vehicle types in Italy sample

Vehicle type	Price levels (€10,000)	Driving range (km)
Petrol	10,12,14,16,18	700, 850, 1000
Diesel	13,16,19,21,24	800, 1000, 1300
LPG	12,14,16,18,20	500, 700, 900
CNG	15,18,20,23,25	300, 600, 900
BEV	18,22,26,30,34	200, 300, 400
PHEV	22,25,28,31,34	800, 1000, 1300
HEV	14,17,20,23,26	900, 1100, 1300

4.3. **Survey experiment design**

4.3.1. **Scenarios generated**

Our efficient design aims to minimize the standard data error in estimated parameters. In this scenario design, we have used the most widely efficient design: D-efficient, to minimize the error of the asymptotic variance-covariance (AVC) matrix to estimate the choice task using the Ngene software (Rose & Bliemer, 2009). As the parameters are fixed in the MNL model, it is necessary to specify a prior parameter for each fixed simulation parameter. However, our pre-test stage has no initial design values; we have developed orthogonal designs in Ngene using prior parameters based on previous studies (Rose & Bliemer, 2009). The prior ones in Italy are based on the survey conducted on 996 respondents in 2018 (Danielis et al., 2020). The prior parameters we used in the Chinese market are based on a survey conducted on 1076 respondents in 2019 (Qian et al., 2019). One example of generated choice scenarios in our survey is shown in Figure 3. All the Ngene codes are listed in Appendix B1.

Prop. system	Petrol	Diesel	LPG	CNG	BEV	HEV	PHEV
Driving range (km)	1,000	1,000	900	300	200	1,100	1,000
Net Price (€)	18,000	16,000	18,000	18,000	30,000	14,000	25,000

Figure 3 An example of choice scenarios proposed to Italian respondents

4.3.2. **Questionnaires design**

The first part aims to collect individual characteristics. In this part, the respondents were asked to provide personal information (e.g., gender, age, job, education level, and household income), car and charging garage availability, and mobility habits. Specifically, the income levels are different in both countries. The real GDP per capita of 2019 in Italy was $3,3215 (ISTAT, 2020), while the real GDP per capita of 2019 in China was $1,0276 (NBSC, 2020); we have divided the annual household income into three levels: low-income, middle-income, and high-income level. Similar rules are set for city sizes, with three city classes in the Italian sample (large city, medium and small city, and rural area) and six city classes in China (super city, huge city, large city, medium city, small city, and rural areas).

The second part focused on revealed choice, aimed to collect information on the characteristics of cars that respondents have bought and used. This part lists seven car types (petrol, diesel, LPG, CNG, HEV, PHEV, BEV). The price range consisted of 12 classes between Italy and China; the minimum purchase price is set according to actual market price levels (€10,000 in Italy and the ¥50,000 in China), and each range increases evenly. To keep the currency consistent, we converted the

Chinese price from the RMB to the Euro (€1=¥8) to maintain parameter comparability across the two countrie[3].

The third part presented different scenarios. Respondents were asked to present their preferred option without providing specific. It is particularly emphasized that the order of net purchase price and driving range in the scenarios was changed twice to confirm whether the preference was influenced by initial impression; finally, we have confirmed no direct impact on the sequence.

The fourth part included different statements related to individual choices of EVs. In particular, we listed 16 statements and a five-point Likert scale to evaluate respondent attitudes: 1—Completely disagree, 2—Partly Disagree, 3—Neither agree nor disagree, 4—Partly agree, and 5—Completely agree. More details are listed in Table 16.

4.4. Conclusion

This chapter includes a comprehensive description of the experiment that has been designed. During the design process, we attempt to retain objectivity, remove the consideration of a certain time periods (e.g., the covid period), and provide an objective and equitable questionnaire design. The primary process for the experiment consisted of three steps: defining alternatives and qualities, generating scenarios, and designing questionnaires. In this experiment, we used seven propulsion systems cars and defined the purchase price and driving range as two attributes. Scenarios were generated using Ngene in each questionnaire, and prior parameters were collected through our pre-test survey. Our questionnaires were standard structured, including four sections: socioeconomic data, revealed preference data collection, stated preference data collection utilizing scenarios, and statements expressed on a five-point Likert scale throughout the questionnaire design process.

[3] The exchange rate is based on the period we conducted our survey between 2021 and 2022. Although the rate has changed, we decided to keep the exchange rate consistent with the previous data collection period.

5. The First Experiment

5.1. **Introduction**

This chapter describes the first choice experiment carried out in February and March 2021 in Italy and China via internet-based interviews. In section 5.2, we collected the revealed and stated preferences data. The respondents were chosen randomly. In sections 5.3 and 5.4, we described the survey in detail, which comprised four parts: socio-economic characteristics, revealed data collection, stated choice scenarios, and statements. Finally, we got the econometric results using the multinomial and mixed logit models (section 5.5).

5.2. **Data collection**

Different samples of Italian (115) and Chinese (201) data were collected via the website during February and March of 2021. The purpose of the survey is to comprehend consumer preferences about automobiles with various power systems, particularly electric vehicles. Finally, we have 1,380 observations in Italy and 2,412 observations in China.

In the beginning, we provided brief instructions to introduce the purpose of the survey. All respondents were asked to choose without any other consideration. All surveys were conducted in privacy protection and were completely anonymous, and the data were dealt with through aggregate processing. The first section collects data on the sociodemographic characteristics, including gender, age, level of education, household income, and garage charging availability. The second section focuses on respondents' revealed preferences (RP). In order to gain a comprehensive understanding of their current car ownership status, respondents were asked to submit details about all cars in their families, including propulsion systems, number of vehicles, price range, driving range, and willingness to purchase electric vehicles. In the third part, respondents were asked to select their preferred automobiles based on the scenarios we generated. In the last part, we included 16 statements on a five-point Likert scale to indicate respondents' perspectives: 1 (Completely disagree), 2 (Partly Disagree), 3 (Neither agree nor disagree), 4 (Partly agree), and 5 (Completely agree). The statements were related to economic factors, charging infrastructures, environmentally conscious attitudes, practical performance, safety concerns, and government incentives.

5.3. **Sample description**

Table 8 describes the demographic characteristics of our samples. The majority of our respondents are younger than 40 years old. Within the average distribution, the proportion of male respondents is slightly greater than that of female respondents. The level of household income differs between the two countries, but the distribution of income is comparable, with the majority of people living in the middle-income class (48.7% vs. 58.2%). The family composition is also the same: small families with three to four members. Most households in both countries own at least one car. In order to reflect the actual demands, we have excluded the driving needs during the specific epidemic period and emphasized respondents' actual driving distance in their daily lives. Most respondents have the same demand; the average driving distance from home to work does not surpass 80 kilometers per day or 20,000 kilometers per year. Surprisingly, more than 20% of respondents in each country paid no attention to the availability of fast charging stations near their place of employment or residence.

The main discrepancy is performed in the sample group. In the Italian survey, most of the respondents were students and much younger. Regarding the area of residence, 39.1% of the Italian respondents live in rural areas, and 93.1% have a garage or parking place. Comparatively, just 9.1% of Chinese respondents reside in rural areas, while up to 33.3% do not own garages or parking places. This can also explain why nearly 70% of respondents had paid attention on recharge availability in China. Moreover, compared with Italy, the proximity to fast charging stations near homes or workplaces in China is also lower (36.8%).

Table 8 Description characteristics of survey sample

	Italy	China
Socio economic information		
Respondents number	115	201
Gender	Male: 69 (60%), Female: 46 (40%)	Male: 110 (54.7%), Female: 91 (45.3%)
Age	18-25: 112(97.4%), 26-30: 2(1.7%), 31-40: 0, 41-50: 1(0.9%), 51-60: 0	18-25: 54(26.9%), 26-30: 58(28.9%), 31-40: 64(31.8%), 41-50: 22(10.9%), 51-60: 3(1.5%)
Education Level	Three years degree: 6(5.2%), Senior school diploma: 109(94.8%)	Post Graduate: 4(2%), Master: 31(15.4%), Bachelor: 60(29.8%), Three years degree: 96(47.7%), Senior school :7(3.5%), Junior school: 3(1.6%)
Current Job	Entrepreneur: 1(0.9%), White collar: 2(1.7%), Student: 110(95.6%), Housewife: 1(0.9%), Other: 1(0.9%)	Entrepreneur: 12(6%), White collar: 46(22.9%), Blue collar: 41(20.4%), Housewife: 1(0.5%), Student: 46(22.9%), Retired: 2(1%), Other: 53(26.3%)
Family annual income	less than €30,000: 52(45.2%), between €30,000 and €70,000: 56(48.7%), more than €70,000: 7(6.1%)	less than ¥100,000:48(23.9), between ¥100,000 and ¥300,000:117(58.2%), more than ¥300,000:36(17.9%)
Family members	1: 1(0.9%), 2: 6(5.2%), 3: 29(25.2%), 4: 66(57.4%), 5: 9(7.8%), More than 5: 4(3.5%)	1:3(1.5%), 2: 13(6.5%), 3: 63(31.3%), 4: 68(33.8%), 5: 40(19.9%), More than 5: 14(7%)
Location		
City size	Large city: 2(1.8%), Small or medium town: 68(59.1%), Rural area: 45(39.1%)	Super cities (more than 10 million inhabitants): 22(10.9%), Very large cities (more than 5 million and less than 10 million inhabitants): 26(12.9%), Large cities (more than 1 million and less than 5 million inhabitants): 31(15.4%), Medium cities (more than 500 thousand and less than 1 million inhabitants): 30(14.9%), Small cities (less than 500 thousand inhabitants): 74(36.8%), Rural areas: 18(9.1%)
Living area	Detached house with a garage or private parking space: 68(59.2%), Detached house without a garage or private parking space: 6(5.2%), Apartment with garage or private parking space: 39(33.9%), Apartment without garage or private parking space: 2(1.7%)	Detached house with a garage or private parking space: 46(22.9%), Detached house without a garage or private parking space: 30(14.9%), Apartment with garage or private parking space: 88(43.8%), Apartment without garage or private parking space: 37(18.4%)
Car and garage ownership		
Garage recharging availability	Yes: 60(52.2%), No: 55(47.8%)	Yes: 61(30.3%), No: 140(69.7%)
Car numbers in the household	0: 1(0.9%), 1: 9(7.8%), 2: 61(53%), 3: 34(30%), more than 4:10(8.3%)	0:23(11.4%), 1:101(50.2%), 2: 52(25.9%), 3: 19(9.5%), more than 4: 6(3%)
Car mobility habits:		
Driving distance per day	≤ 20 km: 31(27%), 20-50km: 53(46%), 50~80 km: 9(7.8%), 80~100 km: 0, ≥ 100 km: 1(0.9%), I don't regularly drive a car: 21(18.3%)	≤ 20 km: 65(32.3%), 20-50km: 42(20.9%), 50~80 km: 13(6.5%), 80~100 km: 6(3%), ≥ 100 km: 4(2%), I don't regularly drive a car: 71(35.3%)
Driving distance in the last 12 months	≤ 5,000 km: 67(58.3%), 5001–10,000 km: 17(14.8%), 10,001–20,000 km: 24(20.9%), 20,001–50,000 km: 6(5.2%), >50,000 km: 1 (0.8%)	≤ 5,000 km: 123(61.2%), 5001–10,000 km: 36(17.9%), 10,001–20,000 km: 32(15.9%), 20,001–50,000 km: 9 (4.5%), >50,000 km: 1(0.5%)
Distance between home-work/education place:	≤ 20 km:47(40.9%), 20-50km: 52(45.2%), 50~80 km: 14(12.2%), 80~100 km: 2(1.7%), ≥ 100 km: 0	≤ 20 km: 159(79.1%), 20-50km: 21(10.4%), 50~80 km: 8(4%), 80~100 km: 0, ≥ 100 km: 13(6.5%)
Proximity to fast charging stations:	Yes: 57(49.6%), No: 33(28.7%), I don't know: 25 (21.7%)	Yes: 74(36.8%), No: 76(37.8%), I don't know: 51(25.4%)

5.4. **Statement comparison in Italy and China**

In our survey, we asked respondents to express their attitudes and norms in accordance with the statements provided. Using a five-point Likert scale, we asked respondents to indicate their level of agreement with 16 statements (1 =“completely disagree”; 2 = “partially disagree”; 3 = “do not know”; 4 =“partially agree”; 5 = “completely agree”). Finally, we received 316 responses from Italy and China (115 vs. 201). We evaluated these statements independently; first, we ranked the 16 attitudes according to their average value, and then we analyzed these statements with socioeconomic factors (Table 10 and Table 11). The rankings are presented in Table 9.

In general, the attitudes in these two countries are distinct. Italians care more about the financial statement: the purchase price. In particular, interacting with sociodemographic variables, respondents in Italy who lived in apartments without a garage were strongly sensitive. One possible explanation related to our Italian sample as the majority of Italian respondents were students and young people. This might imply that our Italian respondents were more cost-sensitive; raising awareness about the financial benefits of promoting EV uptake in Italy would be possible. This is consistent with Danielis et al. (2020) research. Moreover, Italians were more sensitive to “complicated and expensive domestic charging infrastructure”; this may be due to the high cost of owning a garage in urban areas of Italy (Giansoldati, Monte, & Scorrano, 2020). Conversely, Chinese respondents were much more sensitive to range performance; this can be explained by the 30% of people in our sample have no garage or parking place. Retired people, higher education, and housewives were more sensitive to parking hours. This finding is also confirmed as a significant factor in EV adoption (Qian et al., 2019). The other difference between Italy and China is the technology performance of “larger size of battery safety and fire risk”. Although the ranking of this statement is lower in both countries, respondents showed opposite attitudes on this aspect. The Italians were more positive on battery safety, while Chinese people had negative attitude on the battery safety .

Additionally, there are also some similarities between these two countries. Respondents in Italy and China showed great concern for the environment: “driving an electric car is a more environmentally friendly way of transportation than driving a conventional car”. Specifically, females in Italy and those who drove distances between 50km and 80 km per day were more environmental friendly. In addition, males, middle-aged women, retirees, and persons who drive more than 100 km per day in China were more concerned about this issue. In addition, the statement on charging issues (where to charge and at what cost, especially for those who do not own a garage) scored highly in both Italy and China. Respondents in both countries were very sensitive to this aspect. People who lived in apartments without a garage in Italy and who drove more than 100 km per day in China were more likely to agree with this statement. Furthermore, statement on policy incentives caused attention in both countries; specifically, more agreement on “lower purchase price subsidy” among respondents in both countries.

To summarize, the main findings are listed as follows:

- The main difference between these two countries: Italians were more concerned with purchasing price and domestic charging infrastructure, while Chinese were more concerned about limited driving range and parking hours.
- The similities in Italy and China: Both Italian and Chinese agree with the environmental performance. Specifically, female respondents were more sensitive in Italy. Respondents have shown strong sensitivity to charging issues.

Table 9 Statement ranking of average value in Italy and China

	Mean value	
Attitudes	Italy	China
The purchase price is still too high. I prefer to wait.	3.92	3.48
Electric cars have lower maintenance costs than conventional cars.	3.14	3.16
It is not practical to drive an electric car because of the infrequent charging points.	3.70	3.42
The construction of a domestic charging infrastructure is a bureaucratically complicated and expensive process, especially in an apartment.	3.87	3.64
The electric car poses a problem of where to charge and at what cost, especially for those who do not own a garage.	3.99	3.98
Driving an electric car is a more environmental friendly way of transportation than driving a conventional car.	4.19	4.01
I am not convinced that electric cars pollute less than conventional cars due to battery disposal.	2.92	3.51
Long time required for charging an electric car makes the use of electric cars unpractical.	3.30	3.32
Using an electric car requires careful travel planning.	3.86	4.13
I think the performance of an electric car is inferior than the performance of a conventional car.	2.57	3.48
I think electric cars are safer to drive than conventional cars.	2.63	3.07
I would not feel safe driving an electric car given the large size of the battery and considering the risk of fire.	2.26	3.38
I think that the purchasing subsidy for buying an electric car is currently too low.	3.52	3.57
I think the number of free parking hours granted for electric cars enacted by some municipalities is too low.	3.14	3.67
I would enjoy/enjoy driving an electric car more than driving a conventional car.	3.02	3.20
Limited driving range would make/makes me feel uncomfortable to drive an electric car.	3.48	3.82

Table 10 Average values of statements with socio-economic characteristic in Italy

	Gender		Age		Education		Employment					City Size			Housetype				Income		
Statements	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A11	A12	A13	A14	A15	A16	A17	A18	A19	A20	A21
The purchase price is still too high. I prefer to wait.	3.9	4.0	3.9	5.0	4.3	3.9	4.0	4.0	5.0	3.9	5.0	4.0	4.0	3.8	4.0	3.7	3.8	4.0	4.0	4.0	3.9
Electric cars have lower maintenance costs than conventional cars.	3.0	3.2	3.1	3.0	3.2	3.1	3.0	3.5	3.0	3.1	2.0	4.0	3.1	3.1	3.1	4.0	3.1	2.5	3.3	3.0	3.0
The construction of a domestic charging infrastructure is a bureaucratically complicated and expensive process, especially in an apartment.	4.0	3.5	3.7	5.0	3.8	3.7	4.0	3.0	5.0	3.7	3.0	3.0	3.7	3.8	3.5	3.8	4.1	4.0	3.8	4.3	3.6
The electric car poses a problem of where to charge and at what cost, especially for those who do not own a garage.	4.1	3.7	3.9	5.0	4.2	3.9	3.0	4.0	5.0	3.9	3.0	3.0	3.9	3.8	3.6	4.0	4.3	5.0	3.8	4.4	3.9
Driving an electric car is a more environmental friendly way of transportation than driving a conventional car.	4.1	3.9	4.0	5.0	4.3	4.0	4.0	4.0	5.0	4.0	2.0	3.5	4.0	4.0	3.9	4.7	4.1	5.0	3.9	4.4	4.0
I am not convinced that electric cars pollute less than conventional cars due to battery disposal.	4.3	4.1	4.2	5.0	4.3	4.2	4.0	4.5	5.0	4.2	4.0	4.5	4.2	4.2	4.0	4.7	4.4	5.0	4.2	3.4	4.3
It is not practical to drive an electric car because of the infrequent charging points.	3.1	2.8	2.9	5.0	2.8	2.9	3.0	1.5	2.0	3.0	2.0	3.5	2.8	3.0	2.9	2.0	3.1	4.0	2.9	3.1	2.9
Long time required for charging an electric car makes the use of electric cars unpractical.	3.3	3.3	3.3	5.0	3.7	3.3	3.0	2.0	4.0	3.3	2.0	3.0	3.1	3.6	3.3	4.5	3.1	3.5	3.5	3.1	3.2
Using an electric car requires careful travel planning.	3.9	3.8	3.9	5.0	4.2	3.8	4.0	4.0	4.0	3.9	4.0	3.0	3.8	4.0	3.9	3.7	3.8	3.5	3.9	3.3	3.9
I think the performance of an electric car is inferior than the performance of a conventional car.	3.2	2.2	2.6	5.0	2.3	2.6	3.0	2.0	5.0	2.6	1.0	2.0	2.5	2.8	2.6	1.8	2.8	1.0	2.7	2.0	2.5
I think electric cars are safer to drive than conventional cars.	2.6	2.6	2.6	3.0	3.2	2.6	2.0	3.0	3.0	2.6	3.0	3.0	2.6	2.6	2.6	3.0	2.6	2.5	2.7	2.6	2.5
I would not feel safe driving an electric car given the large size of the battery and considering the risk of fire.	2.8	1.9	2.2	5.0	2.0	2.3	3.0	2.0	3.0	2.3	1.0	2.0	2.2	2.4	2.1	2.5	2.4	3.0	2.4	1.9	2.2
I think that the purchasing subsidy for buying an electric car is currently too low.	3.6	3.5	3.5	5.0	3.7	3.5	4.0	3.0	5.0	3.5	4.0	4.5	3.4	3.7	3.4	3.8	3.7	4.0	3.7	3.3	3.4
I think the number of free parking hours granted for electric cars enacted by some municipalities is too low.	3.3	3.0	3.1	3.0	3.5	3.1	3.0	3.5	4.0	3.1	3.0	2.5	3.1	3.3	3.0	4.0	3.3	3.0	3.3	2.7	3.0
I would enjoy/enjoy driving an electric car more than driving a conventional car.	2.9	3.1	3.0	3.0	2.7	3.0	2.0	4.5	3.0	3.0	4.0	4.0	3.0	2.9	2.9	3.3	3.2	2.0	3.1	2.7	3.0
Limited driving range would make/makes me feel uncomfortable to drive an electric car.	3.6	3.4	3.5	5.0	4.2	3.4	4.0	3.5	4.0	3.5	3.0	4.0	3.3	3.7	3.3	4.3	3.7	3.0	3.6	3.4	3.4

Legend: A1: Female; A2: Male; A3: Young; A4: Middle; A5: Three years degree; A6: Senior school degree; A7: Housewife; A8: Employee; A9: Entrepreneur; A10: Student; A11: Other; A12: Large city; A13: Medium and small city; A14: Rural area; A15: Detached house with garage; A16: Detached house without garage; A17: Apartment with garage; A18: Apartment without garage; A19: less than 30,000 euro; A20: Between 30,000 and 70,000 euro; A21: more than 70,000 euro.

	DayKM				YearKM			Car owned number				Charge Ava			Garage Ava	
Statements	B1	B2	B3	B4	B5	B6	B7	B8	B9	B10	B11	B12	B13	B14	B15	B16
The purchase price is still too high. I prefer to wait.	3.9	4.0	4.4	3.5	3.9	4.0	4.4	4.0	3.8	3.9	4.0	4.1	3.8	3.8	3.8	4.0
Electric cars have lower maintenance costs than conventional cars.	2.8	3.2	3.1	3.3	3.3	2.9	2.4	3.0	3.3	3.2	3.0	3.2	3.1	3.0	3.2	3.1
The construction of a domestic charging infrastructure is a bureaucratically complicated and expensive process, especially in an apartment.	3.3	3.8	3.9	4.0	3.7	3.6	3.9	4.0	3.6	3.9	3.5	3.5	3.9	3.9	3.7	3.7
The electric car poses a problem of where to charge and at what cost, especially for those who do not own a garage.	3.8	3.9	3.4	4.0	4.0	3.6	3.7	4.0	4.1	4.0	3.7	3.8	4.0	3.7	4.1	3.7
Driving an electric car is a more environmental friendly way of transportation than driving a conventional car.	3.7	4.0	4.7	4.1	4.0	3.9	4.3	4.0	4.2	4.1	3.8	4.0	3.8	4.2	4.1	3.9
I am not convinced that electric cars pollute less than conventional cars due to battery disposal.	4.3	4.0	4.8	4.4	4.2	4.0	4.4	2.0	4.8	4.5	3.8	4.2	4.5	3.8	4.2	4.2
It is not practical to drive an electric car because of the infrequent charging points.	2.8	3.1	2.4	3.0	3.0	2.9	2.7	4.0	3.0	2.7	3.2	2.7	3.2	3.1	3.0	2.9
Long time required for charging an electric car makes the use of electric cars unpractical.	3.2	3.4	3.8	3.1	3.2	3.5	3.9	3.0	4.0	3.2	3.4	3.2	3.2	3.6	3.2	3.4
Using an electric car requires careful travel planning.	3.7	3.9	4.3	3.8	3.8	4.0	4.6	4.0	4.0	3.8	4.0	3.8	3.7	4.1	3.8	3.9
I think the performance of an electric car is inferior than the performance of a conventional car.	2.2	2.5	3.6	3.0	2.6	2.5	2.9	3.0	2.9	2.7	2.4	2.4	2.8	2.8	2.6	2.6
I think electric cars are safer to drive than conventional cars.	2.9	2.6	2.1	2.4	2.6	2.5	3.3	3.0	2.6	2.7	2.6	2.7	2.6	2.5	2.8	2.5
I would not feel safe driving an electric car given the large size of the battery and considering the risk of fire.	2.0	2.3	2.3	2.5	2.3	2.0	2.3	3.0	2.8	2.3	2.1	2.2	2.4	2.3	2.5	2.1
I think that the purchasing subsidy for buying an electric car is currently too low.	3.3	3.5	4.2	3.6	3.5	3.4	3.7	3.0	4.0	3.5	3.5	3.7	3.5	3.1	3.6	3.5
I think the number of free parking hours granted for electric cars enacted by some municipalities is too low.	3.0	3.1	3.3	3.5	3.1	3.1	3.4	4.0	3.6	3.2	3.0	3.3	2.9	3.1	3.2	3.1
I would enjoy/enjoy driving an electric car more than driving a conventional car.	3.1	2.8	3.0	3.4	3.1	2.8	3.1	4.0	3.2	3.0	3.0	3.1	3.0	3.0	3.1	2.9
Limited driving range would make/makes me feel uncomfortable to drive an electric car.	3.2	3.6	3.4	3.7	3.4	3.5	4.1	4.0	3.6	3.6	3.3	3.5	3.3	3.6	3.5	3.5

Legend: B1: driving range per day less than 20km; B2: driving range per day between 20km and 50km; B3: driving range per day between 50km and 80km; B4: I don't often use a car; B5: driving range per year <=10000km; B6: between 10000km to 20000km; B7: more than 20000km; B8: No owned car; B9: One owned car; B10: Two owned car; B11: Three and More than three owned car; B12: Can charge; B13: Cannot charge; B14: Not clearly; B15: Have a garage; B16: No garage

Table 11 Average values of statements with socio-economic characteristic in China

	Gender		Age			Education level						Employment							City Size					
Statements	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17	C18	C19	C20	C21	C22	C23	C24
The purchase price is still too high. I prefer to wait.	3.5	3.5	3.4	3.8	5.0	3.8	3.2	3.5	3.5	3.1	4.7	3.3	3.5	3.8	1.0	3.4	4.5	3.4	3.8	3.5	3.5	3.3	3.5	3.4
Electric cars have lower maintenance costs than conventional cars.	3.1	3.2	3.1	3.3	5.0	3.3	3.0	3.3	3.2	2.1	3.7	3.4	3.1	3.2	1.0	3.4	4.0	3.0	3.0	3.2	3.2	2.9	3.3	2.9
The construction of a domestic charging infrastructure is a bureaucratically complicated and expensive process, especially in an apartment.	3.1	3.7	3.4	3.5	5.0	4.5	3.4	3.3	3.5	3.0	2.3	3.4	3.4	3.5	1.0	3.3	3.0	3.5	3.0	3.7	3.6	3.3	3.6	2.9
The electric car poses a problem of where to charge and at what cost, especially for those who do not own a garage.	3.5	3.8	3.6	3.9	5.0	4.0	3.6	3.6	3.7	3.9	4.3	3.5	3.6	3.6	5.0	3.6	5.0	3.7	3.2	3.7	3.5	3.8	3.7	3.7
Driving an electric car is a more environmental friendly way of transportation than driving a conventional car.	3.8	4.1	3.9	4.3	5.0	4.8	4.0	3.9	4.0	3.9	5.0	4.1	3.9	4.1	5.0	3.9	5.0	3.9	4.1	4.2	4.0	3.8	4.0	3.6
I am not convinced that electric cars pollute less than conventional cars due to battery disposal.	4.0	4.1	3.9	4.6	5.0	4.3	3.8	3.9	4.1	3.9	5.0	3.4	4.0	4.2	5.0	4.0	5.0	3.9	4.2	4.2	3.6	4.0	4.0	4.3
It is not practical to drive an electric car because of the infrequent charging points.	3.4	3.6	3.5	3.5	1.0	3.8	3.7	3.5	3.6	2.7	2.3	3.3	3.5	3.3	1.0	3.6	2.0	3.7	3.4	4.0	3.6	3.1	3.6	2.8
Long time required for charging an electric car makes the use of electric cars unpractical.	3.1	3.5	3.4	3.0	3.0	4.3	3.6	3.4	3.2	2.7	2.3	3.5	3.5	3.3	1.0	3.4	2.5	3.2	3.2	3.5	3.5	3.0	3.5	2.9
Using an electric car requires careful travel planning.	4.0	4.3	4.1	4.4	5.0	5.0	4.2	4.1	4.1	3.6	5.0	3.7	4.1	4.3	5.0	4.1	5.0	4.1	4.1	4.5	4.0	3.9	4.1	4.3
I think the performance of an electric car is inferior than the performance of a conventional car.	3.4	3.6	3.4	3.8	3.0	3.8	3.3	3.5	3.6	2.6	5.0	3.6	3.3	3.7	2.0	3.5	4.0	3.5	3.4	3.4	3.3	3.1	3.8	3.1
I think electric cars are safer to drive than conventional cars.	3.1	3.1	3.0	3.3	5.0	2.3	2.8	3.2	3.1	2.6	4.3	3.2	2.9	3.2	2.0	3.3	5.0	2.8	2.7	3.0	3.3	2.9	3.2	2.8
I would not feel safe driving an electric car given the large size of the battery and considering the risk of fire.	3.2	3.5	3.4	3.3	4.0	4.0	3.2	3.5	3.4	2.6	3.0	3.6	3.3	3.3	3.0	3.5	4.0	3.4	3.2	3.5	3.4	3.1	3.6	2.9
I think that the purchasing subsidy for buying an electric car is currently too low.	3.5	3.6	3.6	3.7	4.0	3.3	3.2	3.7	3.7	3.3	1.7	3.1	3.6	3.6	1.0	3.5	4.0	3.7	3.6	3.5	3.6	3.4	3.7	3.3
I think the number of free parking hours granted for electric cars enacted by some municipalities is too low.	3.6	3.7	3.7	3.8	5.0	3.0	3.3	3.7	3.8	3.9	3.0	3.5	3.7	3.6	5.0	3.6	4.0	3.7	3.6	3.6	3.7	3.7	3.7	3.5

I would enjoy/enjoy driving an electric car more than driving a conventional car.	3.2	3.2	3.1	4.0	5.0	2.0	2.9	3.1	3.4	3.4	5.0	2.9	3.1	3.5	5.0	3.3	5.0	2.9	3.0	3.0	3.3	3.0	3.4	2.9
Limited driving range would make/makes me feel uncomfortable to drive an electric car.	3.7	3.9	3.8	3.8	1.0	4.5	4.0	3.7	3.8	3.7	3.3	3.7	3.9	3.8	5.0	3.8	2.5	3.9	3.7	4.3	3.7	3.6	3.9	3.3

Legend: C1: Female; C2: Male; C3: Young; C4: Middle; C5: Old; C6: PhD; C7: Master; C8: Bachelor; C9: Three year degree (professional); C10: Senior school degree; C11: Junior school degree; C12: Entrepreneur; C13: White collar; C14: Employee; C15: Housewife; C16: Student; C17: Retired; C18: Other; C19: Super large city; C20: Very large city; C21: Large city; C22: Medium city; C23: Small city; C24: Rural area

	Housetype				Income			Garage ownership		Car owned number				Charge Ava			YearKM			DayKM					
Statements	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D11	D12	D13	D14	D15	D16	D17	D18	D19	D20	D21	D22	D23	D24	D25
The purchase price is still too high. I prefer to wait.	3.4	3.8	3.5	3.2	3.6	3.5	3.4	3.5	3.5	3.7	3.5	3.5	3.1	3.6	3.5	3.4	3.5	3.5	3.1	3.5	3.5	3.5	3.5	3.5	3.5
Electric cars have lower maintenance costs than conventional cars.	3.5	3.4	3.0	3.0	3.1	3.1	3.4	3.1	3.2	3.3	3.1	3.2	3.3	3.1	3.2	3.1	3.2	3.2	2.7	3.1	3.1	3.5	3.2	4.0	3.1
The construction of a domestic charging infrastructure is a bureaucratically complicated and expensive process, especially in an apartment.	3.4	3.5	3.4	3.6	3.4	3.4	3.4	3.2	3.5	3.6	3.3	3.5	3.4	3.0	3.7	3.6	3.4	3.7	2.9	3.5	3.6	3.5	3.2	4.5	3.2
The electric car poses a problem of where to charge and at what cost, especially for those who do not own a garage.	3.8	3.7	3.6	3.6	3.7	3.6	3.6	3.4	3.8	3.8	3.6	3.6	3.6	3.4	3.8	3.7	3.7	3.5	3.2	3.5	3.5	3.8	3.7	4.8	3.7
Driving an electric car is a more environmental friendly way of transportation than driving a conventional car.	4.1	3.9	3.9	4.1	4.0	3.9	4.3	3.9	4.0	4.1	3.8	4.2	4.0	3.8	4.2	3.9	4.0	4.1	3.5	4.0	3.9	4.2	4.2	4.5	3.9
I am not convinced that electric cars pollute less than conventional cars due to battery disposal.	4.1	4.1	4.1	3.8	4.1	4.0	4.0	3.9	4.0	4.0	4.0	4.1	3.8	3.9	4.3	3.7	4.0	4.1	4.5	4.0	3.7	4.4	4.5	4.5	4.0
It is not practical to drive an electric car because of the infrequent charging points.	3.4	3.6	3.5	3.5	3.3	3.5	3.9	3.5	3.5	3.5	3.5	3.4	3.8	3.6	3.5	3.5	3.5	3.5	3.1	3.6	3.4	3.5	4.0	3.8	3.5
Long time required for charging an electric car makes the use of electric cars unpractical.	3.3	3.3	3.3	3.5	3.2	3.3	3.6	3.3	3.3	3.6	3.1	3.3	3.8	3.1	3.4	3.5	3.4	3.3	3.0	3.3	3.5	3.5	2.5	3.8	3.3

Using an electric car requires careful travel planning.	4.1	4.2	4.1	4.1	3.9	4.2	4.4	4.0	4.2	4.3	4.0	4.3	4.3	4.1	4.3	4.1	4.1	4.3	3.9	4.2	4.1	4.1	3.8	3.8	4.2
I think the performance of an electric car is inferior than the performance of a conventional car.	3.5	3.6	3.5	3.4	3.4	3.6	3.4	3.6	3.5	3.5	3.4	3.6	3.4	3.5	3.5	3.5	3.5	3.4	3.8	3.4	3.5	3.5	3.7	4.3	3.5
I think electric cars are safer to drive than conventional cars.	3.4	3.4	2.8	3.0	3.2	3.0	3.1	3.2	3.0	3.4	3.0	3.0	3.2	3.0	3.1	3.2	3.1	2.7	3.0	2.9	3.0	3.5	3.0	4.0	3.1
I would not feel safe driving an electric car given the large size of the battery and considering the risk of fire.	3.4	3.5	3.3	3.4	3.3	3.4	3.5	3.3	3.4	3.6	3.3	3.3	3.7	3.4	3.3	3.4	3.4	3.3	3.3	3.3	3.3	3.4	4.2	4.5	3.3
I think that the purchasing subsidy for buying an electric car is currently too low.	3.6	3.7	3.5	3.6	3.5	3.6	3.5	3.4	3.7	3.8	3.5	3.5	3.6	3.4	3.7	3.6	3.6	3.5	3.6	3.4	3.6	3.5	4.8	3.5	3.6
I think the number of free parking hours granted for electric cars enacted by some municipalities is too low.	3.7	3.9	3.6	3.6	3.7	3.7	3.7	3.5	3.7	3.9	3.7	3.4	3.9	3.6	3.7	3.6	3.7	3.6	3.1	3.5	3.6	3.4	4.3	4.5	3.8
I would enjoy/enjoy driving an electric car more than driving a conventional car.	3.4	3.5	3.1	3.0	3.5	3.1	3.2	3.4	3.1	3.4	3.2	3.1	3.3	3.1	3.4	3.1	3.2	2.9	3.4	3.1	3.0	3.5	3.8	3.8	3.3
Limited driving range would make/makes me feel uncomfortable to drive an electric car.	3.8	3.8	3.8	3.9	3.8	3.8	3.9	3.8	3.8	4.0	3.8	3.9	3.8	3.8	3.9	3.7	3.8	3.8	3.8	3.8	3.6	3.6	4.3	4.0	4.0

Legend: D1: Apartment with garage; D2: Apartment without garage; D3: Detached house with garage; D4: Detached house without garage; D5: Less than 10wan rmb; D6: Between 10wan and 30wan rmb; D7: More than 30w rmb; D8: Garage availability; D9: No garage; D10: No owned car; D11: One owned car; D12: Two owned car; D13: Three and more than three owned car; D14: Can charge; D15: Cannot charge; D16: Not clearly; D17: driving range per year <=10000km; D18: between 10000km to 20000km; D19: more than 20000km; D20: driving range per day less than 20km; D21: driving range per day between 20km and 50km; D22: driving range per day between 50km and 80km; D23: driving range per day between 80km and 100km; D24: driving range per day more than 100km; D25: I don’t often use a car.

5.5. **Model Specification Results**

5.5.1. **Multinomial logit model (MNL) model result**

The findings of the MNL model are listed in the Table 12. The MNL model was estimated with the Apollo package in R. To maintain parameter comparability between the two countries, we have converted the Chinese price (RMB) to the Euro (€1 = ¥8). We examined the scale parameter in relation to the value 1; the results indicated that the scale parameter (λ=1.646) was not significantly different from one, we could not reject the null hypothesis that the variance of the data was significantly different, confirming that the two samples had the same variance. All estimated coefficients were significantly different between the two countries.

Overall, the value of Rho_square is 0.24, the whole model fitness is good. Petrol cars, *ceteris paribus*, are still considered reference cars. The coefficient of ASC_BEVs in Italy is significantly positive, implying that people in Italy have a high utility on BEVs. While the coefficient of ASC_BEVs in China is negative, indicating that Chinese respondents place a lower utility on BEVs.

The coefficient of the purchase price on BEVs was significant negative as expected; more specifically, Italians were more price sensitive. As the average yearly income in Italy is larger than in China, this is not easily explained; we will further explore by examining with some socioeconomic variables in the following survey. The coefficient of driving range on BEVs in China is significantly positive, implying that extended driving range would cause higher utility for Chinese respondents. This is consistent with the finding by Qian et al. (2019), which also confirms that Chinese consumers could buy BEVs based on a longer driving range. Whereas it is not statistically significant in Italy, this might indicate that Italian respondents in our sample should do more understanding work on this variable; the result was consistent with the research by Kormos et al. (2019). Although the coefficient of driving range in our subsamples is very slightly, we cannot assume that driving range does not have a substantial effect in respondents' decisions; we will do additional analysis in the following step.

Table 12 MNL results with scale parameter

	Italy			China		
	Estimate	Rob.s.e.	Rob.t.rat.(0)	Estimate	Rob.s.e.	Rob.t.rat.(0)
asc_petrol	0.000	NA	NA	0.000	NA	NA
asc_diesel	0.327**	0.159	2.059	-1.475***	0.138	-10.669
asc_lpg	-0.055	0.169	-0.322	\	\	\
asc_cng	-0.849***	0.314	-2.701	\	\	\
asc_bev	2.351***	0.826	2.845	-1.215***	0.261	-4.656
asc_hev	0.367**	0.192	1.910	-0.355***	0.085	-4.163
asc_phev	-0.893***	0.289	-3.090	-0.872***	0.125	-7.000
b_price	-0.147***	0.013	-10.955	-0.012***	0.006	-1.830
b_range_ice	0.004***	0.000	13.455	0.001***	0.000	4.731
b_range_bev	0.0002	0.002	-0.100	0.002***	0.001	3.106
Scale parameter (λ)[a]				1.646[a]	0.115	14.315
Summary statistics						
Number of individuals	316					
Estimated parameters	17					
Number of observation	3792					
LL(0)	-6567.32					
LL(final)	-4999.927					
Rho-square	0.2387					
AIC	10033.85					
BIC	10139.95					

Notes: * Statistical significance at the 10% level.

** Statistical significance at the 5% level.

*** Statistical significance at the 1% level or smaller.

a : The t-test of the scale factor is computed with respect to a value of 1. The value of 1 indicates no scale difference.

5.5.2. **Mixed Logit model (MXL) reslut**

We considered random parameters with the stated preference data in this section. In order to identify the best model, we examined a variety of specifications with random parameters, including BEV, purchase price, and driving range. Finally, we used the best model with random parameters of BEV, price, and range. Table 13 lists the model results. The pseudo-R^2 is 0.3704, which is statistically acceptable for this class of model, the overall model fit is good. To describe preferences on a country-specific level, we tested the scale parameter with respect to the value of 1. The scale paremeter was not significantly different from one, confirming that the two sample had the same covariance; all the coefficients we estimated were significantly different between the two countries.

Petrol cars, *ceteris paribus*, were still considered reference cars. To capture the heterogeneity preference for BEVs, we implemented random parameters with BEVs. The coefficient of standard deviation for BEV is highly significant, indicating heterogeneity preference exsited in our samples. Specifically, the coefficients for ASC_BEV was significantly negative, indicating lower utility of BEVs on avearage. Specifically, Chinese were more sensitive on BEVs. For the attributes of the purchase price and driving range, each of them was given randomly independent normal distribution with mean μ and standard deviation σ (Equation **14** and **15**). The standard deviation of each random coefficient was highly significant, respectively, indicating that heterogeneity in price and driving range existed over the samples. In particular, the mean value of purchase price in Italy was higher than that in China, indicating that Italians were more sensitive on purchase price, high purchase price would reduce the uptake of BEVs. The mean driving range of BEVs was significant positive, implies the extend range would increse the uptake of BEVs.

Table 13 Mixed logit model results

	Italy		China	
	Coeff.	S.E.	Coeff.	S.E.
asc_petrol	0	NA	0	NA
asc_diesel	0.292**	0.115	-2.319***	0.190
asc_lpg	-0.107	0.112	\	\
asc_cng	-0.976***	0.236	\	\
mu_asc_bev	-1.311*	0.861	-7.338***	1.283
sigma_asc_bev	1.656***	0.367	-4.128***	0.694
asc_hev	0.379**	0.139	-0.518***	0.138
asc_phev	-1.631***	0.305	-1.616***	0.152
mu_b_price	-0.158***	0.020	-0.031**	0.014
sigma_b_price	-0.146***	0.015	-0.181***	0.017
mu_b_range_ice	0.005***	0.000	0.000***	0.000
sigma_b_range_ice	-0.004***	0.000	0.002***	0.000
mu_b_range_bev	0.007***	0.002	0.006***	0.002
sigma_b_range_bev	-0.002**	0.001	0.007***	0.001
Scale parameter [a]	1.187(0.066) [a]			

Note: scale parameter a: compared with the value of 1; * Statistical significance at the 10% level; ** Statistical significance at the 5% level; *** Statistical significance at the 1%level or smaller.

5.6. **Conclusions**

This chapter illustrated the first expressed preference experiments for electric vehicles to be conducted in Italy and China in 2021. The aim is to evaluate the possible impact of attributes on consumer purchase decisions. We have used MNL and MXL models to estimate the results in both countries.

The main discrepancy in the sample description is the availability of garage charging. For our Italian survey, most of the respondents were students and much younger; almost all of the respondents had a garage or parking place for charging, while up to 33.3% of the Chinese respondents did not own garages or parking places. The attitudes also differ between these two countries. Italians cared more about financial attributes: as to the purchase price, they strongly agreed with the purchase price of electric cars being high and preferred to wait. At the same time, the Chinese respondents paid more attention to a non-financial attribute: range performance. The finding is consistent with the research by R. Danielis et al. (2020) and Qian et al. (2019).

From the estimated results, heterogeneity peference existed on BEVs in both countries. Chinese respondents were more likely to reject BEVs. The purchase price and driving range played crucial roles in both countries. Italians were more price sensitive, while the Chinese were more range sensitive. Although the Italian government has implemented some policy incentives (such as "Ecobonus") on electric cars (Scorrano & Danielis, 2021b), primary problem in Italian market was still related with price subsidies (Rotaris et al., 2020). While in China, increased driving range would promote the uptake of BEVs (Qian et al., 2019).

Despite our respondents were selected randomly, the sample data collected in these two countries was significantly different. Thus, it was difficult to analyze and compare the significantly different variables and characteristics between two samples. We will improve the database collection and conduct a new experiment in both countries in the next step.

6. The Second Experiment: Description and Factor Analysis

6.1. **Introduction**

This chapter focuses on the experiment that compared the preferences of EVs in the survey. The study aims to identify similarities and differences in the car choices of respondents, confirming the determinant factors in encouraging consumer acceptance of EVs in both countries. For the experiment, we focused on the younger group to demonstrate which specific attributes combined with policy initiatives would be more effective for future trends. In Section 6.2, we described the data collection methodology, including the design of stated choice experiments, attribute levels, and the data collection process. Then in Section 6.3, we briefly described the characteristics of two subsamples. In Section 6.4, we provided a detailed description of factor analysis, including data evaluation, factor extraction, factor retention criteria, the rotation method, model fitness evaluation, and the interpretation of the results. Then, we introduced the factor analysis methodology in our study (section 6.5) and briefly described attitudes in both countries (section 6.6). Finally, we reported the econometric results and factor analysis interpretation (section 6.7).

6.2. **Data collection**

The data collection was performed by web-based version which was conducted from March to November 2021. The respondents were all above 18 years old. Data were collected from a total of 436 respondents in Italy and 358 respondents in China after excluding incomplete or inaccurate responses. Before the formal data collection, we conducted a pre-test in a small group of respondents from the two countries who could understand better the EV questionnaire, to identify possible misunderstandings, presentation issues, and potential errors.

The questionnaire had four parts. In the first part, the purpose of the survey was briefly described as to investigate their preference among cars with different propulsion systems. The survey was conducted with privacy protection and was completely anonymous, and all the data were aggregated for processing.

The first and second parts of the questionnaire were focused on the socio-economic characteristics and car choices of the respondents, such as gender, age class, education level, annual income, availability of a garage or parking place for charging, driving distance per day/year, price range, driving range, annual distance traveled, and willingness to buy an EV. The third part reflected on the SP information. The attributes selection in our stated-choice experiments was a critical process, the detailed selection rules was listed in Section 4.2, the detailed process of generated scenarios was listed in Section 4.3.1. Since customer preferences may differ and attributes may be perceived differently across various powertrain cars, we generated 24 scenarios using Ngene software. The priori estimates were derived from our pre-test survey conducted in Italy and China in 2021. Each scenario included seven propulsion systems: petrol cars, diesel cars, liquefied propane gas (LPG), compressed natural gas (CNG), BEV, HEV, and PHEV. One example of choice scenarios in our survey is shown in Figure 4. The price level and range level in both two countries are reported in Table 14 and Table 15. The fourth part includes different statements on EV choices (Table 16).

Propulsion system	Petrol	Diesel	LPG	CNG	BEV	HEV	PHEV
Driving range (KM)	400	1.100	500	800	200	1.000	1.000
Purchase price (€)	10.000	24.000	20.000	25.000	30.000	26.000	31.000

Figure 4 Examples of choice scenarios

Table 14 Price levels and range levels of automobiles in Italian sample

Vehicle type	Price level (€10,000)	Driving range (km)
Petrol	10, 12, 14, 16, 18	700, 850, 1000
Diesel	13, 16, 19, 21, 24	800, 1000, 1300
LPG	12, 14, 16, 18, 20	500, 700, 900
CNG	15, 18, 20, 23, 25	300, 600, 900
BEV	18, 22, 26, 30, 34	200, 300, 400
PHEV	22, 25, 28, 31, 34	800, 1000, 1300
HEV	14, 17, 20, 23, 26	900, 1100, 1300

Table 15 Price levels and range levels of automobiles in Chinese sample

Vehicle type	Price level (¥10,000)	Driving range (km)
Petrol	90, 110, 130, 150, 170	700, 850, 1000
Diesel	120, 140, 160, 180, 200	800, 1000, 1300
BEV	90, 130, 150, 200, 250	400, 500, 600
PHEV	130, 160, 180, 220, 250	800, 1000, 1300
HEV	110, 130, 150, 170, 200	900, 1100, 1300

Table 16 Statements listed in questionnaire

Item with direction	Statements presented in questionnaire
Less economic incentives Q1(-)	"The purchase price is still too high. I prefer to wait."
Less economic incentives Q2(+)	"Electric cars have lower maintenance costs than conventional cars."
Lack of charging infrastructure Q3(-)	"It is not practical to drive an electric car because of the infrequent charging points."
Lack of charging infrastructure Q4(-)	"The construction of a domestic charging infrastructure is a bureaucratically complicated and expensive process, especially in an apartment."
Lack of charging infrastructure Q5(-)	"The electric car poses a problem of where to charge and at what cost, especially for those who do not own a garage."
Environment awareness Q6(+)	"Driving an electric car is a more environmental friendly way of transportation than driving a conventional car."
Environment awareness Q7(-)	"I am not convinced that electric cars pollute less than conventional cars due to battery disposal."
Limited driving range Q8(-)	"Long time required for charging an electric car makes the use of electric cars unpractical."
Limited driving range Q9(-)	"Using an electric car requires careful travel planning."
Not perfect driving performance Q10(-)	"I think the performance of an electric car is inferior than the performance of a conventional car."
Not perfect driving performance Q11(+)	"I think electric cars are safer to drive than conventional cars."
Not perfect driving performance Q12(-)	"I would not feel safe driving an electric car given the large size of the battery and considering the risk of fire."
Less economic incentives Q13(-)	"I think the purchasing subsidy for buying an electric car is currently too low."

Less economic incentives Q14(-)	"I think the number of free parking hours granted for electric cars enacted by some municipalities is too low."
Not perfect driving performance Q15(+)	"I would enjoy driving an electric car more than driving a conventional car."
Limited driving range Q16(-)	"Limited driving range would make/makes me feel uncomfortable to drive an electric car."

6.3. **Sample description**

The survey was carried out in both Italy and China. All respondents were asked to complete the survey through the provided online link. Both samples have met the requirements for factor analysis sample size, which indicated that the sample size of 100 can be adequate under a good condition of 0.7 or greater with four or five variables per item, moderate conditions of 0.40 to 0.70 commonalities with 200 sizes were also reasonable (MacCallum, Widaman, Zhang, & Hong, 1999). Descriptive statistics of the entire sample are summarized in Table 17.

The sample is quite balanced between the two countries: 55% observations have been collected in Italy and 45% in China. The Italian sample included 54.8% male and 45.2% female respondents, the same as the gender proportion in the Chinese sample. The age distribution, education level, and occupation are quite similar for the two countries. Both samples consisted mainly of young people aged 18 to 25 years, and most of them were studying at a university. The proportion of the reported household net annual income, which was less than €70,000 in Italy, was higher than that in China.

One of the main differences is in the charging infrastructure in the two countries because the availability of public charging points near workplace or home in Italy is lower than that in China. This evidence is consistent with the findings of Rotaris et al. (2020), which confirmed the obstacle of fast charging points in the Italian market (Giansoldati, Monte, et al., 2020). But interestingly, the portion of private garage availability in Italy has reached to 55.5%, much higher than that in China. This is also found in the recent research of Danielis et al. (2020), which confirmed that garage ownership plays a positive role on EVs. The second difference is reflected in individual mobility habits, with Italians driving more than Chinese: 11.3% of Italian respondents drive more than 20,000 km per year, which is confirmed as the threshold on the driving distance of cost-competitive performance of EVs by Scorrano et al. (2020) in their recent study. Almost two-thirds of the Italian respondents commute long distances (more than 100 km) between home and work place, which necessitates dense network of fast charging stations or a more extended driving range of BEVs. However, only 3.9% of people in China drive more than 50 km to their workplaces, and more than half of the respondents do not usually use a car every day. Thus, such people would not pay much attention to fast charging infrastructures or longer driving ranges. The third one is in terms of car ownership. Surprisingly, almost all families in Italy own at least one car, and 46.1% of Italians have three cars and more in their family, which is much higher than that in China with only 7.8%. This reflects the considerable market potential for the uptake of EVs in the Italian car market (Danielis et al., 2020), as people who have already owned their first car are more likely to choose new technology cars when they have a choice to buy their second or third cars (Qian et al., 2019; Qian & Soopramanien, 2011).

Figure 5 lists the actual choices of car ownership. The preferences of respondents between two countries are significantly different. Petrol cars were the most preferred car for both countries, but the share of petrol cars in China is much higher than that in Italy. Ownership of diesel cars comes second in Italy, while it is much lower in China. Both countries have a low uptake on BEVs. Interestingly, although the actual choices are different in the two countries, the share of car ownership for the respondents interviewed is high in both. Surprisingly, almost all the Italian families have at least one car, 46.1% of them have more than three cars, much higher than that in China, which is only 7.8%. This might reflect the huge potential market of EVs in Italy (Danielis et al., 2020), as the Italian respondents who already had a car were more inclined to choose alternative-fuel vehicles than conventional cars for their second or third car (Qian et al., 2019; Qian & Soopramanien, 2011). The Italian respondents also preferred diesel cars, while the share of diesel cars in China was very low. However, the real market share of BEVs in the whole car market in both two countries is still very low.

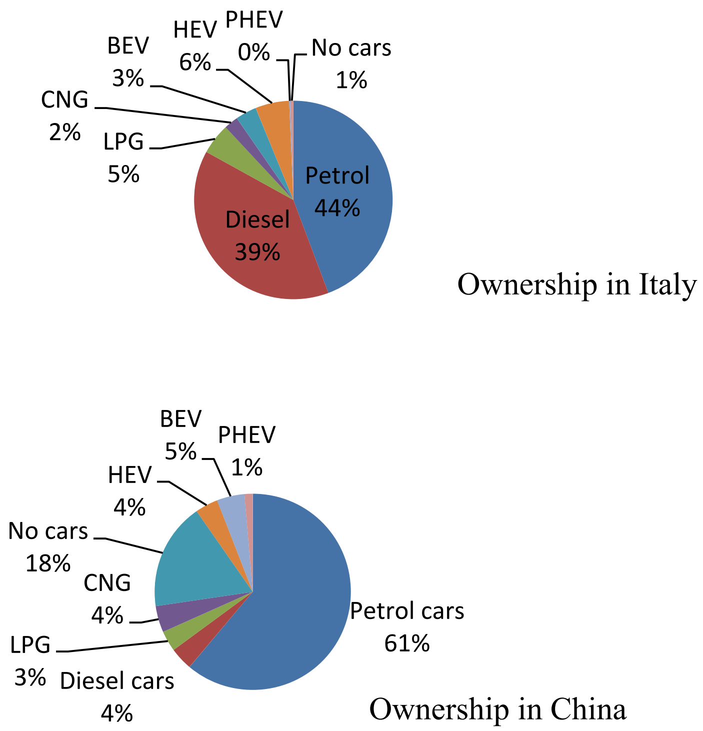


Figure 5 Overview of the car ownership (RP choice)

Table 17 Summary of data description in Italy and China

	Italy	China
Socio economic information		
Respondents number	436	358
Gender	Male:54.8% (239), Female:45.2% (197)	Male:51.96% (186), Female:48.04% (172)
Age	18-25: 86.4% (377), 26-30: 6% (26), 31-35: 1.6% (7), 36-40: 1.8% (8), >40: 4.1% (18)	18-25: 96.9%(347), 26-30:2.8% (10), 31-35:0.3% (1)
Education Level	Senior: 75.9%(331), Four-year university degree:4.1 %(18), Three-year university degree:19.7 %(86), Master: 0.2%(1)	Four-year university degree:69.8%(250), Three-year university degree:21.2%(76), Master and PhD degree:9%(32)
Family annual income	less than €30,000: 43.8%(191), between €30,000 and €70,000: 49.1%(214), more than €70,000: 7.1%(31)	less than ¥100,000: 41.3%(148), between ¥100,000 and ¥300,000: 47.2%(169), more than ¥300,000: 11.5%(41)
Family structure	1 people: 2%(9), 2 people: 6.8%(29),3 people:28.4% (124), 4 people:47.7%(208), 5 people and more:15.1%(66)	3 people:34.5% (124), 4 people:35.5%(127), 5 people and more:27.1%(97), less than 3 pepole:2.9%(10)
Location		
City size	Big city:2.1% (9), Middle and small city:58.7%(256), Rural area:39.2%(171)	Big city (Permanent population of more than 1 million):46.1% (165), Middle and small city:41.3%(148), Rural area:12.6%(45)
House type (garage)	Detached house with garage:62.6%(273), Detached house without garage:3.5%(15), Apartment with garage:29.1%(127), Apartment without garage:4.8%(21)	Detached house with garage:18.1%(65), Detached house without garage:20.4%(73), Apartment with garage:36.1%(129), Apartment without garage:25.4%(91)
Car and garage ownership		
Private garage charging availability	Yes: 55.5%(242), No: 44.5% (194)	Yes: 41.1%(147), No: 58.9% (211)
Numbers of car ownership	No car: 0.5%(2), One car: 10.7%(47), Two cars: 42.7%(186), Three and more: 46.1%(201)	No car: 10.9%(39), One car: 57.8%(207), Two cars: 23.5%(84), Three and more cars: 7.8%(28)
Car mobility habits:		
Driving distance per day	≤ 20 km: 25.5% (111), 20-50km: 37.6% (164), 50-80km: 12.8% (56), 80-100km: 2.1%(9), >100km: 2.1%(9), I don't use a car: 19.9%(87)	≤ 20 km: 31.3% (112), 20-50km:8.4% (30), >50km: 3.9% (14), I don't use a car: 56.4%(202)
Driving distance in the last 12 months	≤10,000 km: 68.3%(298), 10,000-20,000km: 20.4%(89), >20,000km: 11.3%(49)	≤10,000 km: 96.6%(346), 10,000-20,000km: 2.2 %(8), >20,000km:1.2 %(4)
Distance between home-work/education place:	≤ 20 km: 14.4%(63), 20-50km: 14.9%(65), 50~80 km: 4.8%(21), 80~100 km: 1% (4), ≥ 100 km: 64.9% (283)	≤ 20 km: 76%(272), 20-50km: 8.1%(29), 50~80 km: 2.2% (8), 80~100 km: 2% (7), ≥ 100 km: 11.7%(42)
Proximity of fast charging stations:	Not clearly: 22.9% (100), No public charging point: 30.3% (132), Have public charging points: 46.8%(204)	Not clearly: 25.4% (91), No public charging point: 21.2% (76), Have public charging points: 58.9%(211)

6.4. Attitudes description

The summarized statistical description of attitudes between Italy and China are listed in Table 18. We found that respondents in both of two countries paid great attention to charging infrastructure and driving range, with 80% of them partly or completely agreeing with the charging issue of EVs. The respondents were sensitive to charging points and the cost of charging. This can also explain the anxiety attitudes on the need for carefully planning travel for most of the respondents in the two countries. This finding is consistent with the research of Y. Yang et al. (2016) and Rotaris et al. (2020). In addition, respondents in both countries partially agreed with the economic obstacles of EVs. Among the Italian respondents, almost 80% partly agreed on the high purchase price of EVs, while more than 75% of the Chinese respondents were concerned about the high cost. The Chinese respondents also agreed more with the statement on insufficient policy incentives. Furthermore, the majority of respondents from both Italy and China paid a great deal of attention to environmental issues, and they partly agreed with the statement that driving EVs was more environment friendly. Specifically, 83% of the Chinese respondents agreed that EVs played a significant role in reducing environment pollution. This can be explained by the serious environmental pollution problem in China. Among all the items, the attitude on driving performance was given the least importance in both Italy and China, with more than half of the respondents providing neutral responses to the questions regarding operational performance and safety.

Table 18 Descriptive statistics of the indicators

	mean		sd		median		min		max		kurtosis		skew	
	IT	CN	IT	CN	IT	CN	IT	CN	IT	CN	IT	CN	IT	CN
Q1	3.94	3.56	0.93	1.02	4	4	1	1	5	5	0.14	-0.26	-0.68	-0.36
Q2	3.12	3.32	1.1	1.1	3	3	1	1	5	5	-0.51	-0.66	0.09	-0.15
Q3	3.72	3.46	1.12	1.09	4	4	1	1	5	5	-0.47	-0.62	-0.61	-0.35
Q4	3.75	3.81	1.08	1.05	4	4	1	1	5	5	-0.35	-0.29	-0.54	-0.67
Q5	4.09	4.03	0.95	0.91	4	4	1	1	5	5	0.16	0.4	-0.89	-0.79
Q6	3.85	4.13	1.22	0.99	4	4	1	1	5	5	-0.46	-0.01	-0.78	-0.88
Q7	3.14	3.42	1.33	1.1	3	3	1	1	5	5	-1.21	-0.73	-0.09	-0.2
Q8	3.28	3.15	1.16	1.2	3	3	1	1	5	5	-0.9	-0.95	-0.21	-0.04
Q9	4.05	4.07	0.92	0.98	4	4	1	1	5	5	0.03	0.23	-0.78	-0.92
Q10	2.36	3.22	1.22	1.21	2	3	1	1	5	5	-0.65	-0.81	0.55	-0.13
Q11	2.69	2.98	1.04	1.1	3	3	1	1	5	5	-0.16	-0.46	0.21	0.06
Q12	2.09	3.25	1.03	1.06	2	3	1	1	5	5	-0.06	-0.59	0.71	-0.16
Q13	3.52	3.48	0.99	1.03	3	3	1	1	5	5	-0.39	-0.42	-0.14	-0.23
Q14	3.12	3.81	0.99	0.94	3	4	1	1	5	5	0.14	0.2	0.06	-0.63
Q15	3.29	3.06	1.35	1.16	3	3	1	1	5	5	-1.05	-0.69	-0.3	0.06
Q16	3.39	3.66	1.17	1.09	4	4	1	1	5	5	-0.68	-0.4	-0.41	-0.52

6.5. **Theories of factor analysis criterion**

Factor analysis originated at the beginning of the 20th century with the work of Pearson (1901), which was the first detailed description of the factor analysis technique. Traditionally, it uses mathematical techniques to explore potential underlying structures in a set of interrelated variables (Child, 2006). The theoretical model for factor analysis is the standard factor model, which determines correlation patterns by observing measures affected by underlying common factors and unique factors. There are two variables in factor analysis: observed and latent variables. Latent variables share a common variance but are challenging to detect and cannot be directly measured; factor analysis aims to reduce the number of observed variables to a smaller number of latent variables. The assumption is that variables have a continuous, multivariate normal distribution. The factor analysis is performed by using R.

The two principal factor analyses are exploratory factor analysis (EFA) and confirmatory factor analysis (CFA). Exploratory factor analysis is crucial for identifying the fundamental structure of a set of observed variables. According to Child (2006), EFA is a technique for identifying the number of latent constructs and the underlying factor structure of variables. It can estimate the factors that influence the response to the observed variables and describe and identify the number of latent factors, including error items. However, it would keep the preconceived structure of results the same. CFA is a technique for validating factor structures based on a set of observed factors. Before conducting structural equation modeling (SEM), researchers will examine the measured model to confirm whether measured variables accurately reflect factors or not (Jackson, Gillaspy Jr, & Purc-Stephenson, 2009). The main difference between EFA and CFA is that CFA uses factors to validate a predetermined structure, whereas EFA employs variables to discover structure. If the factor structures are not confirmed, EFA will be performed in the following steps.

The analytical guide is based on the work of Thompson (2004) and follows the stages outlined in Williams, Onsman, and Brown (2010) and Watkins (2018). divided the key procedures into the following steps: determining whether the data is acceptable for factor analysis, how to extract factors, factor extraction criteria, rotation method, model fit evaluation, factor interpretation, and factor labeling.

6.5.1. **Data evaluation**

The data assumption is assumed to be univariate and multivariate normality (Child, 2006). Another assumption is linearity between factors (smaller than observed variables) and observed variables, which can explain correlations between observed variables and underlying variables (Pett, Lackey, & Sullivan, 2003). In addition, additivity is used to check whether the variables are correlated in order to proceed with the analysis.

The sample size is an essential part of factor analysis; a limited sample size easily causes bias during the estimation process. However, there is minimal consensus among academics on this point. Hair (2009) suggested that the sample size should be at least 100. Comrey and Lee (2013) have pointed out the guidelines for evaluating the sample size: they have considered 100 cases to be poor, 200 to be a fair number, more than 300 to be good, and 1000 or more to be excellent. Tabachnick, Fidell, and Ullman (2007) recommend at least 300 samples for factor analysis; however, if the factor loading is greater than 0.80, 150 samples are adequate. Pett et al. (2003) suggested at least 10 to 15 items per category, following the fit index of very good to excellent. Participants-to-variable ratios of 5:1 have been strongly suggested by Reio Jr and Shuck (2015), at least with 100 cases or greater. Furthermore, according to Kahn (2006), decisions on sample size should examine the number of variables and their rational structure. MacCallum et al. (1999) have indicated that a sample size of 100 can be adequate under reasonable conditions of 0.7 or greater with four or five variables per item; moderate conditions of 0.40 to 0.70 commonalities with 200 sizes were also reasonable.

In addition to sample size, the correlation matrix is evaluated using the factorability of the correlation matrix, commonly known as the factorability of R. According to Tabachnick et al. (2007), coefficients of correlation matrices over 0.30 are acceptable. The values with less than 0.30 are considered weak loadings, and will be eliminated (Pett et al., 2003).

Furthermore, somel tests are performed to evaluate correlation adequacy, confirming good correlations to categorize into factors or components. These tests include Bartlett's test for correlation adequacy and Kaiser-Meyer-Olkin (KMO) measure for sampling adequacy. For factor analysis, Bartlett's Test should be significant ($p<0.05$). The KMO values range from 0.00 to 1.00; values closer to 1 are preferred; a KMO value of 0.50 is considered appropriate for factor analysis (Thompson, 2004), and a value of 0.70 is desirable (Watkins, 2018).

In summarizing prior research, it is stated that less than 100 participants is unacceptable, that 300 is the optimal number, and that 10 to 15 participants per item are recommended. Morover, the structural coefficient is regarded as a fundamental rule. Under inadequate conditions, no sample size is adequate to generate an accurate estimate. A correlation matrix greater than 0.30 is generally acceptable. Bartlett's test ($p<0.05$) should be statistically significant, a Kaiser-Meyer-Olkin (KMO) value of 0.5 is suitable, and a value of 0.7 is preferred for testing correlation adequacy.

6.5.2. **Factor extraction**

Variances are used to generate commonalities between variables in factor analysis. The commonality is the variance of observed variables that is explained by the common variance, which is the overlapping variance between items (Child, 2006). It is the sum of the squared correlations of the variables and factors, denoted by h^2, and its expression is $h_j^2 = a_{j1}^2 + a_{j2}^2 + \cdots + a_{jm}^2$, where a_{jm} is the loading for j variables, which represents the contribution that j variable makes to each factor a_{jm}. The communality calculation reveals what proportion of these j variables can be predicted. Typically, variations with low communalities are eliminated (< .20). The purpose of factor extraction is to simplify the component structure of groups of items; the method is to to eliminate as much common variation as feasible from the first factor. The other main variance is the unique variance. The variance excluding common variance is denoted by $\mu^2 = 1 - h^2$. Specific variance and error variance comprise the two components of unique variance. The total variance consists of the common variance, the specific variance, and the error variance. EFA is used to describe the common variance, while principal component analysis (PCA) is used to describe the total variance.

There are a large number of extraction methods; the most common are principal component analysis (PCA), principal axis factoring (PAF), and maximum likelihood (ML) (Hair, 2009; Kahn, 2006; Thompson, 2004). Principal components analysis (PCA) is a method to reduce the number of components by extracting the maximum variance from the data set for each component (Tabachnick et al., 2007). Therefore, PCA can create components; some researchers use PCA as the initial stage in data reduction. Principal axis factoring (PAF) is a method for calculating the residual matrix when all variables are identified as belonging to the first group and factors are extracted. Generally, it is recommended to use PAF when data sets violate the assumption of multivariate normality (Costello & Osborne, 2005). Maximum Likelihood (ML) is a method for assessing the likelihood of the correlation matrix by conducting significance tests and deriving confidence intervals for multivariate normal data.

There are no conclusive results about the extraction procedure. Kahn (2006) has found that 45% of the reviewed works used PAF to extract factors, 32% used PCA, and 18% used ML from 2002 to 2005 in the studies of EFA. When variables have high reliability, Thompson (2004) found no significant between PCA and PAF when variables had good dependability. It is appropriate to apply the ML approach when the sample size is big, variables follow to multivariate normality, and the relationship between factors and variables is sensitive (>.40) (Watkins, 2018). Thus, it is better to select an extraction technique based on research and interpretation.

6.5.3. **Criteria of factor retain**

Extracting too many factors might cause error variance, whereas extracting too few factors might result in omitting common variance. The purpose of factor retention criteria is to maintain the model's simplicity and completeness. The most common selection rules are Kaiser's criteria (eigenvalues >1 rule or 0.70), the scree test, parallel analysis, and a priori theory (Reio Jr & Shuck, 2015). Eigenvalues are the amount of variance explained by each principal component or factor. The rule of eigenvalues (EV) > 1 indicates that eigenvalues greater than one are interpreted as a factor. However, it is easily to overestimate the number of elements or components if an excessive number of factors are extracted (Henson & Roberts, 2006).

The scree test is a graphical tool that depicts the number of eigenvalues by factor count in decreasing order. By drawing a straight line over the smaller eigenvalues that deviate from this line, it is possible to identify substantial drop-offs and confirm the factor numbers. The parallel analysis compares actual eigenvalues to random order eigenvalues; when actual eigenvalues are greater than random eigenvalues, factors are retained. In a parallel analysis, three lines are listed: a dark line, a blue line, and a red line. The dark line is set to one, which is a component of the Kaiser criterion; the red dotted line represents the random dataset, which is randomly reordered to determine how many factors are superior to chance. The blue triangular lines represent the actual dataset's eigenvalues; by checking the intersection where the blue line and red line cross, it is possible to confirm the number of factors. The method of parallel analysis is usually used in combination with the scree plot test. A priori theory is also an essential criterion for determining the predicted number of elements from the scale. It must be plausible on a theoretical level. Researchers conduct EFA using criteria that are supported by the theory.

However, the number of the final extracted factors is determined by multiple considerations. These principles provide some theoretical suggestions for factor extraction; researchers should also consider the objective of the research and design specifications.

6.5.4. **Factor rotation method**

The following step is to rotate factors to assist interpretation after selecting the number of extracted factors. In general, factor rotation aims to obtain a simple structure by rotating the axes within factor space to bring factors closer to the location of variables, and obtain smaller residuals without altering mathematical properties, attempting to keep variable loadings as low as possible while maximizing the number of variables with high loadings. By factor rotation, high item loadings are maximized and low item loadings are minimized. Two typical rotation techniques are orthogonal and oblique rotation (Tabachnick et al., 2007). Assuming there is no association between the factors, orthogonal rotation occurs when the factor axes are rotated to a 90° angle. In orthogonal rotation, variance rotation is the predominant technique.

Variance rotation maximizes the sum of the variances of the squared loadings to determine the structural coefficient pattern. The factors are kept orthogonal, and the eigenvalues of the rotated factors are more evenly rotated after variance; therefore, this method can generate the same correlations between variables as the unrotated structural coefficients. When the factor axes are not rotated to a 90° angle and the factors are correlated, this is called as oblique rotation. Two types of factor loadings are obtained by conducting an oblique rotation: structural and pattern coefficients. Correlations between common components and measured variables are structure coefficients; the values of structure coefficients are greater when the factors are highly connected. Correlations between common factors and measured variables are represented by pattern coefficients. Pattern coefficients may exceed one, but they cannot be squared to determine the fraction of variance contributed by common components (Watkins, 2018). When the factors are correlated, the values of pattern coefficients and structure coefficients diverge (Kahn, 2006).

Although different rotations might produce different results, researchers should also evaluate the exact rotation based on their hypotheses regarding the variables and the interpretability of the factors. If there are only two or fewer variables among the rotational components, they should be interpreted with caution. When there is only one factor with two variables, it can be considered reliable when the variables are highly correlated with each other ($r > 0.70$) but relatively uncorrelated with other variables (Yong & Pearce, 2013). Variables over 0.30 may only be loaded onto one factor. When rotating factors are confirmed, researchers will evaluate the variables that are not loaded onto a factor or are loaded onto two or more factors before deciding whether to get rid of them or not.

6.5.5. **Model fit evaluation**

After data evaluation, factor extraction, and factor rotation, the model fit was examined to evaluate whether the entire process was appropriate. The fit of the model can be determined by comparing the actual covariance of variables to the underlying covariance of parameter estimations (Bollen, 1989). There are some fit indices to measure how well the rotated matrix matches the original matrix. Chi-square indices can reflect the goodness of fit statistics between the reproduced and real correlation matrix. The larger the differences between reproduced and actual variances, the higher the chi-square statistic indice. Thus, the higher chi-square indicates a more significant difference between the simulated model and actual data. The significant p-value means a poor model fit.

Several fit indices are used to evaluate model fit. The non-normed fit index (NFI) or Tucker-Lewis index (TLI) and the comparative fit index are used to evaluate the model's fit (CFI). The values range from 0 to 1, and Monte Carlo analysis suggests that values greater than 0.90 indicate good, values greater than 0.95 indicate excellent, while values less than 0.90 indicates poorness (Hu & Bentler, 1999). The other two indices to reflect the goodness of residual fit are the root mean square error of approximation (RMSEA) and the mean root square of the residual (RMSR). RMSEA and RMSR values less than 0.08 indicate a model with a good fit, while values less than 0.06 indicate an excellent fit. The fit indices are listed in Table 19. In addition, reliability—the estimation of how many items "go together" and replicate—should also be considered. The reliability value ranges from 0 to 1; larger numbers indicate more excellent reliability. The most frequent evaluation index is

Cronbach's alpha. There are various recommendations for acceptable alpha values ranging from 0.70 to 0.95. A low number of questions, poor interrelations, and heterogeneous structure can result in a low alpha value. Higher alpha values (> 0.90) suggest redundancy; hence, the length of the test should be shorten (Tavakol & Dennick, 2011).

Table 19 Goodness of fit statistics and Residual statistics

Fit	**Name**	**Excellent**	**Acceptable**	**Poor**
NNFI/TLI	Non-normed fit index, Tucker-Lewis index	>.95	>.90	<.90
CFI	Comparative fix index	>.95	>.90	<.90
RMSEA	Root mean square error of approximation	<.06	.06-.08	>.10
RMSR	Root mean square of the residual	<.06	.06-.08	>.10

6.5.6. Interpretation and named for factors

The final and most crucial step is the output interpretation. It is a cautious and accurate procedure. Kahn (2006) outlined the rules and procedures for interpretation: describe samples in detail, including all pertinent information about variables, such as a description of variables (means and standard deviations), types of correlation, factor extraction method, criteria for factor retention, initial eigenvalues, an explanation of the proportion of variance attributable to each factor, factor rotation types, and structure coefficients. Researchers should examine the goodness of model fitness and factor reliability. If the factors are reasonable and adequate, researchers will create in accordance with their theoretical and conceptual objectives. Table 20 summarizes the entire factor analysis process.

Table 20 Guidelines of Information to Include Factor Analysis Report

Steps	Information
Data Accuracy checked	• Check out basic information: values, participants,sample size • Data characteristics measured: reverse items, data distribution • Missing data checked • Outliers : find false data then omit them
Additivity checked	Correlation matrix analysis: r < .999
Set up Assumption	Use fake regression analysis
Normality checked	Check standardized, linearity, homogeneity and homoscedasticity
Correlation and sample adequacy	Bartlett's test (p<.05), KMO (close to 1)
Factor extraction	Estimtion method: ML (>.40)
Factor to retain	Criteria: Theory, Parallel, Kaiser criterion (eigenvalue > 1)
Factor rotation	Techniques: orthogonal rotation and oblique rotation Rules: simple model structure (each loading are only on one factor and >0.30)
Model fit	Goodness of fit indices: NNFI/TLI, CFI Residual indices: RMSEA, RMSR Reliability: Cronbach's alpha (0.7 or 0.8 is acceptable)

6.6. Factor Analysis Methodology

Behavior patterns play crucial roles in the study of EVs adoption, but they are difficult to describe and evaluate directly; they include customers' knowledge, psychological aspects, and personality traits. Typically, they are used as a latent construction in research (Scorrano & Danielis, 2021a). The factor analysis model is a multivariate model that assumes linear regression in order to predict the primary latent or unobserved factors. The formula for the simple linear regression function is:

$$\boldsymbol{y_i = \tau_i + \lambda_i \eta + \epsilon_i} \quad 19$$

where τ_i is the intercept of the items' intercepts or means and λ_i is the loading or regression weight of the factors on the items, which can be interpreted as the correlation of the item with the factor. η is the unobserved latent predictor of the items, whereas predictors in a linear regression are observed, and ϵ_i is the items residual.

Then the function can be present as a matrix equation:

$$\begin{pmatrix} \boldsymbol{y_1} \\ \boldsymbol{y_2} \\ \vdots \\ \boldsymbol{y_i} \end{pmatrix} = \begin{pmatrix} \boldsymbol{\tau_1} \\ \boldsymbol{\tau_2} \\ \vdots \\ \boldsymbol{\tau_i} \end{pmatrix} + \begin{pmatrix} \boldsymbol{\lambda_1} \\ \boldsymbol{\lambda_2} \\ \vdots \\ \boldsymbol{\lambda_i} \end{pmatrix} (\boldsymbol{\eta}) + \begin{pmatrix} \boldsymbol{\epsilon_1} \\ \boldsymbol{\epsilon_2} \\ \vdots \\ \boldsymbol{\epsilon_i} \end{pmatrix} \quad 20$$

The variance-covariance matrix is a model-implied covariance matrix that is used to explain interrelationships between observed and underlying factors. The variance-covariance formula is as follows:

$$\boldsymbol{\Sigma(\theta) = \Lambda\Psi\Lambda' + \theta_\epsilon} \quad 21$$

Where Λ is the factor loading matrix from the measurement model, Ψ is the variance-covariance matrix of the latent factor, the same as η, θ_ϵ is the variance-covariance matrix of the residuals.

6.7. **Factor Analysis Results**

6.7.1. **EFA results and interpretation**

Firstly, we have a basic summary for all 16 statements. Kurtosis is used to measure whether the data is heavy-tailed or light-tailed in comparison to a standard normal distribution, skewness is used to reflect symmetry. The values of skewness and kurtosis in our studies are reasonable, implying that all of the questions can partly reflect the useful information. In order to maintain accuracy for all of the questions, we reversed the items to make sure the high scores matched the low scores on other questions. We have reversed the following questions : Q1, Q3, Q4, Q5, Q7, Q8, Q9, Q10, Q12, Q13, Q14, and Q16. We also checked for missing data and false data; there are no missing data in our samples, but 4 multivariate outliers in Italy and 8 false data points in China were detected by using the Mahalanobis distance ($\chi^2(16) = 39.25$), so we removed them in the next analyses. We have used Bartlett's test and KMO test to check the adequacy of correlation and sampling. According to the Bartlett's test (IT: $\chi^2(120) = 1597.81$, CN: $\chi^2(120) = 1269.66$, p <.001), and the sampling was adequate, according to the KMO test (MSA = 0.81), the correlation was adequate.

Then, we conducted analysis to extract and retain a number of independent and interpretable factors from these 16 items. We used an oblimin rotation to extract the underlying factors due to correlations among predicted factors. Then we checked eigenvalues to determine the number of elements to retain. Varied criteria have provided different ideas for factor analysis. The Kaiser criteria suggested two factors, both in Italy and China; parallel analysis suggested six factors in Italy and four factors in China, we have decided to use four factors in both countries and cluster the statements into four groups based on the loading criteria of greater than 0.40. These four factors can explain almost half of the variance. The final model has a simple structure, with each item focusing on only one fitness factor. The model goodness indices in both countries show that the final model fit was excellent (IT: TLI=0.997, CFI=0.999, RMSEA=0.013, RMSR=0.01; CN: TLI=0.961, CFI=0.991, RMSEA=0.039, RMSR=0.02). The reliability of all factors is good (IT: 0.72, 0.7, 0.67, 0.51; CN: 0.69, 0.63, 0.65, 0.59). The results of the factor analysis are listed in Table 21.

In Italy, Factor 1 included Q8, Q9, and Q16, which represent attitudes concerning the limited driving range and long charging times on EVs. Factor 1 was labeled as “Not skeptical of EVs”. They all have a significant positive loading on this factor, which means consumers in Italy have paid great attention to the driving range of BEVs. They have a consistent agreement on the attitude of limited driving range. Factor 1 accounts for the largest proportion of the total variance, indicating consumers will pay more attention to driving range when they choose EVs. Anxiety associated with a limited driving range would be more sensitive (Sheldon et al., 2017). Factor 2 included Q6 and Q7, indicating awareness about the environment. This factor was labeled as “EVs are not environmentally friendly”. Factor 3 included Q3, Q4, and Q5. They are all related to infrequent charging infrastructures, so we gave it the label “not sufficient charging infrastructure”. This factor has the highest correlation with factor 1, “Not skeptical on EVs”, indicating that the limited driving range of EVs would cause more attention to charging points. Factor 4 included Q13 and Q14, both of which are focused on policy incentives. Respondents agree with the insufficient current incentives for EVs.

In China, factor 1 “not being skeptical of EVs” included questions Q8, Q10, and Q12, which focused on the attitude regarding the limited driving range and safety of EVs. Factor 2, “good performance on EVs”,included Q2, Q11, and Q15, which are focused on lower maintenance costs and safe driving performance on EVs. Factor 3 is included in Q3 and Q4; they are both related to limited charging infrastructures, so we give a label of “insufficient charging infrastructure”. Factor 4 included Q13 and Q14, both of them focused on “insufficient policy incentives”.

Table 21 EFA result in Italy and China

Italy						China					
Factor loadings											
Item	Statement	ML1	ML2	ML3	ML4	Item	Statement	ML1	ML2	ML3	ML4
Q8	Long time required for charging an electric car makes the use of electric cars unpractical	0.8				Q8	Long time required for charging an electric car makes the use of electric cars unpractical	0.55			
Q9	Using an electric car requires careful travel planning	0.6				Q10	I think the performance of an electric car is inferior than the performance of a conventional car	0.68			
Q16	Limited driving range would make/makes me feel uncomfortable to drive an electric car	0.63				Q12	I would not feel safe driving an electric car given the large size of the battery and considering the risk of fire	0.6			
Q6	Driving an electric car is a more environmental friendly way of transportation than driving a conventional car		0.68			Q2	Electric cars have lower maintenance costs than conventional cars		0.43		
Q7	I am not convinced that electric cars pollute less than conventional cars due to battery disposal		0.8			Q11	I think electric cars are safer to drive than conventional cars		0.82		
Q3	It is not practical to drive an electric car because of the infrequent charging points			0.45		Q15	I would enjoy driving an electric car more than driving a conventional car		0.51		
Q4	The construction of a domestic charging infrastructure is a bureaucratically complicated and expensive process, especially in an apartment			0.51		Q3	It is not practical to drive an electric car because of the infrequent charging points			0.8	
Q5	The electric car poses a problem of where to charge and at what cost, especially for those who do not own a garage			0.77		Q4	The construction of a domestic charging infrastructure is a bureaucratically complicated and expensive process, especially in an apartment			0.51	
Q13	I think the purchasing subsidy for buying an electric car is currently too low				0.56	Q13	I think that the purchasing subsidy for buying an electric car is currently too low				0.59
Q14	I think the number of free parking hours granted for electric cars enacted by some municipalities is too low				0.56	Q14	I think the number of free parking hours granted for electric cars enacted by some municipalities is too low				0.65
SS loadings		1.59	1.16	1.18	0.81	SS loadings		1.28	1.17	1.12	0.90
Proportion Var		0.16	0.12	0.12	0.08	Proportion Var		0.13	0.12	0.11	0.09
Cumulative Var		0.16	0.27	0.39	0.47	Cumulative Var		0.13	0.25	0.36	0.45
Factor correlations											

Factor 1	1				Factor 1	1			
Factor2	0.49	1			Factor2	-0.08	1		
Factor3	0.51	0.19	1		Factor3	0.56	0.01	1	
Factor4	0.22	0.01	0.3	1	Factor4	0.3	-0.38	0.31	1
Fitness Index									
NNFI/TLI	0.997				NNFI/TLI	0.961			
CFI	0.999				CFI	0.991			
RMSEA	0.013				RMSEA	0.039			
RMSR	0.01				RMSR	0.02			
Reliability	Factor 1(Q8,Q9,Q16)	0.72			Reliability	Factor 1(Q8,Q10,Q12)	0.69		
	Factor 2(Q6,Q7)	0.7				Factor 2(Q2,Q11,Q15)	0.63		
	Factor 3(Q3,Q4,Q5)	0.67				Factor 3(Q3,Q4)	0.65		
	Factor 4(Q13,Q14)	0.51				Factor 4(Q13,Q14)	0.59		

6.7.2. **CFA results and interpretation**

We employed CFA in structural equation modeling to examine whether or not the component observed through EFA is appropriate with the model structure. The results are listed in Table 22.

Firstly, we evaluated the data. We carried out a basic statistical summary; the statistic values, including skewness and kurtosis, are reasonable, indicating that the questions listed in our survey can capture useful information. All of the variances are positive, the values of the R-square are all less than 1, and the standard errors are not large, indicating the logic of our model is reasonable. To validate the measurement model, we measured its convergent validity by checking the average variance extracted (AVE). If the normalized factor load value of all articles (Std.all) is greater than 0.30, it has shown strong correlations among latent variables. The values of Q2 (Std. all = 0.272) and Q11 (Std. all = 0.289) in our sample are less than 0.3, so we excluded them in the next analysis. Then, we utilized the modification index for a single parameter based on the chi-square test to improve model fit. It has shown that Q3 and Q5 have equality constraints in the model, and considering the value of chi-square, we opted to eliminate Q5. By deleting Q2, Q5, and Q11, we have achieved a preliminary construction.

Then we confirmed the model construction by testing the reliability and model fit. Cronbach's alpha, RMSEA, SRMR, TLI, and CFI were used as indices. Finally, we dropped Q2, Q4, Q5, Q11, and Q14 to maximize the structure's accuracy. Thus, We obtained an appropriate structure for the hypothesized model in four groups: charging and range, environment, economics, policy incentives, and driving performance. Factors 1 (0.75), 2 (0.43), 3 (0.7), and 4 (0.56) have good reliability, indicating that the data were reliable and consistent. The variance of the four factors is 0.369, 0.527, 0.538, and 0.328, indicating our database can adequately explain the four factors. The four factors have accounted for 47% of the total variance. our model is excellent as the root mean square of the residuals (RMSR) is 0.02. The statistical results indicated that our four-factor model is the most adequate structure.

In the Italian sample, factor 1 includes Q3, Q8, Q9, and Q16. It describes the respondents' attitude on limited driving range and insufficient charging infrastructure. We labeled it as "Not skeptical on EVs". The variables Q3, Q8, Q9, and Q16 are all positive loadings on factor 1, which accounts for the largest proportion (19%) of total explained variances, indicating that respondents in our samples pay great attention to the issue of driving range and charging infrastructure when they have chosen EVs. Factor 2 included Q1 and Q13, which accounted for 12% of the total variance, indicating respondents agreed with the insufficient policy subsidies on the high purchase price of EVs. Q1 has a positive loading on factor 2, while Q13 has a negative loading. As both of these attitudes are focused on economic policies, we labeled them "late adopters". Factor 3 includes Q6 and Q7, accounting for a 12% share of the total variance, and is described as the awareness of environmentally friendly choices. Q3 and Q6 has negative factor loading, whereas Q7 has positive factor loading. In order to main consistency between two statements on the factor group, we reversed Q7 and renamed it Q7A. This is to ensure that high scores correspond to low scores in Q6, then Q7A is defined as “I am convinced that electric cars pollute less than conventional cars due to battery disposal”. This factor is labeled “EVs are not environmentally friendly”. Factor 4 consists of Q10, Q12, and Q15, and it accounts for 7% of the variance. Q10 and Q15 are both focused on driving performance, showing negative loadings on factor 4, while Q12, the one on the safety performance of EVs, has a positive loading. We also reversed Q15 to make sure the high-scoring answers corresponded with the low-scoring answers of Q10 and Q12. Then Q15A is named as “I would not enjoy driving an electric car more than driving a conventional car”. We labeled it as “fast, safe, and fun to drive”.

The CFA factor analysis was also carried out on a Chinese sample. We assigned a value of 0.4 to the factor retain, which allowed us to classify the statements into three groups. The distinction between Italy and China is determined by the environmental consciousness, which is labeled “EVs are not environmentally friendly”. In China, environmental awareness factors are not sensitive; we cannot cluster into a single group. However, the factor of “EVs are not environmentally friendly” factor in Italy explains most of the total variance, indicating that environmental awareness is important for Italians when choosing BEVs. We will use the hybrid choice model to test the factor analysis results in the following part.

6.8. **Conclusion**

In this section, we carried out an experiment on the younger group in both countries to compare commonalities and differences in the car choices. We finally collected 436 data points in Italy and 358 in China via a web-based survey, after deleting the invalid ones. Petrol cars were the preferred car for both countries, specifically in China. Most of the respondents paid great attention to the limited charging infrastructure; this is in line with the research by Y. Yang et al. (2016) and Rotaris et al. (2020). Environment awareness is still relevant for both countries.

Exploratory factor analysis (EFA) and confirmatory factor analysis (CFA) are conducted in factor analysis. We provided 16 most reliable statements. Four items were identified in Italy and three items were identified in China, labeled as “Not skeptical about EVs”, “Late adopters”, “EVs are not environmentally friendly”, “EVs are fast, safe and fun to drive”. All of them are statistically significant, indicating that all of the extracted variables played important roles in the choice of EVs. In particular, the factor that “EVs are not environmentally friendly” in Italy explains the majority of the total variance, indicating that environmental awareness plays a significant role in the choice of BEVs. Recent research has proven that those with a greater focus on global environmental issues are more likely to participate in an environmental event due to the positive effects of environmental awareness (Danielis et al., 2020; Rotaris et al., 2020; Scorrano & Danielis, 2021a).

Table 22 CFA Results in Italy and China

Italy							**China**						
	Estimate	Std.Err	z-value	P(>|z|)	Std.lv	Std.all		Estimate	Std.Err	z-value	P(>|z|)	Std.lv	Std.all
Not skeptical on EVs =~							**Not skeptical on EVs =~**						
Q3:infrequent charging points	1	\	\	\	0.608	0.546	Q3:infrequent charging points	1	\	\	\	0.678	0.633
Q8:long charging time	1.513	0.145	10.411	0.000	0.92	0.795	Q4:bureaucratically domestic charging	0.967	0.103	9.382	0.000	0.656	0.644
Q9:carful on travel planning	0.875	0.099	8.808	0.000	0.532	0.576	Q5:where to charge and at what cost	0.671	0.084	7.948	0.000	0.455	0.52
Q16:limited driving range	1.327	0.135	9.838	0.000	0.806	0.694	Q8: long charging time	1.129	0.121	9.338	0.000	0.765	0.64
Late adopters =~							Q9: carful on travel planning	0.674	0.091	7.388	0.000	0.457	0.477
Q1:high purchase price	1	\	\	\	0.726	0.801	Q16: limited driving range	0.858	0.103	8.297	0.000	0.582	0.548
Q13:low subsidy	0.467	0.158	2.952	0.003	0.339	0.346	**Late adopters =~**						
EVs are not environmentally friendly =~							Q1: high purchase price	1	\	\	\	0.448	0.445
Q6:environmental friendly	1	\	\	\	0.734	0.599	Q13: low subsidy	1.479	0.256	5.772	0.000	0.663	0.658
Q7:not convinced on pollution	1.602	0.192	8.338	0.000	1.175	0.891	Q14: low free parking hours	1.188	0.209	5.693	0.000	0.532	0.587
EVs are fast, safe and fun to drive =~							**EVs are fast, safe and fun to drive =~**						
Q10:inferior performance	1	\	\	\	0.573	0.472	Q10: inferior performance	1	\	\	\	0.709	0.597
Q12: not safety	0.931	0.131	7.108	0.000	0.533	0.528	Q12: not safety because of battery	0.977	0.129	7.597	0.000	0.693	0.667
Q15:enjoy driving	1.482	0.192	7.729	0.000	0.849	0.631							

7. The Second Experiment: Econometric Results

7.1. **Introduction**

In this chapter, we used three models: the multinomial logit model (MNL), the mixed logit model (MXL), and the hybrid mixed logit model (HMXL) to estimate the results of choices. In Section 7.2, we estimated the stated preference data by using the MNL model that interacted with socio-economic characteristics. In Section 7.3, considering random parameters, we used the MXL model with socio-economic interactions to obtain findings. Finally, we used the hybrid mixed logit model to explore the role of attitudes (section 7.4).

7.2. **MNL results**

The MNL results are listed in Table 23. The alternative specific constants (ASCs) were used to capture the average effect of all the factors for an alternative that were not included in the models (Train, 2009). We interacted ASC_BEV with socioeconomic variables: gender, income, city size, the living distance between the home and the work or study place, and garage charging availability.

In general, the adjusted R-squared values were 0.247 and 0.129 in Italy and China, respectively, indicating that the overall model fitness was good. Columns A and C show the results of the basic MNL model without socioeconomic variables. Columns B and D report the results, adding the socioeconomic variables in the two countries. Comparing Columns A and B for the Italian sample with Columns C and D for the Chinese sample shows that the signs of the ASCs in the two countries are relatively stable. In our samples, petrol cars, *ceteris paribus*, are considered reference cars. For the basic MNL specifications without socioeconomic variables, the coefficients associated with BEVs were significantly positive in the two countries, implying that, *ceteris paribus*, the respondents in both countries had a positive attitude to EVs. All the attributes were significant and had the expected signs in the two countries. The coefficient of the purchase price was significantly negative, indicating that higher prices would decrease the utility of BEVs for the respondents. The coefficient of the driving range was also statistically positive, implying that an increased driving range would also increase the utility of BEVs. This was also confirmed by Danielis et al. (2020) and Y. Huang and Qian (2018). Specifically, the estimated coefficient of price showed Italians were more price sensitive.

Then, we considered the impacts of the socioeconomic characteristics on the choices of BEVs. We observed that the garage charging availability played a significant positive role on consumer choices of BEVs in both Italy and China, *ceteris paribus*, which means that the respondents with garage charging capability had a more positive attitude to BEVs than those who do not have a garage. Specifically, the Italian respondents were more sensitive than the Chinese respondents. This contradicts the finding of Danielis et al. (2020) that garage ownership did not significantly affect reduce the TCO. Moreover, among the Italian samples, men were more likely to choose BEVs than women. This is contrary to the finding of Rotaris et al. (2020) that gender was not statistically significant for the Italian respondents. The preference for BEVs was higher among the Italian respondents who lived in large cities than among their Chinese counterparts. Income played a significant role in Italy while there was no significant sign in China. People who have high-income level in Italy were more likely to choose BEVs. This result was in line with those of Rotaris et al. (2020), who also confirmed on the role of the income level in comparison studies. However, none of these variables were confirmed the significant effects on the choice of EVs for Chinese respondents.

Table 23 Results of MNL model

	Italy		**China**	
	Coefficient (s.e.)		**Coefficient (s.e.)**	
	A	**B**	**C**	**D**
Asc_petrol	0	0	0	0
Asc_diesel	-0.200***(0.049)	-0.196***(0.049)	-2.046***(0.059)	-2.049***(0.177)
Asc_lpg	-0.516***(0.052)	-0.513***(0.052)	\	\
Asc_cng	-1.496***(0.125)	-1.491***(0.125)	\	\
Asc_bev	1.705***(0.290)	0.783**(0.341)	0.474(0.183)	0.633* (0.380)
Asc_hev	0.359***(0.058)	0.362***(0.058)	0.014 (0.042)	0.015 (0.073)
Asc_phev	-0.746***(0.119)	-0.735***(0.119)	-0.578***(0.059)	-0.572***(0.120)
b_price	-0.134***(0.006)	-0.135***(0.006)	-0.134***(0.000)	-0.135***(0.000)
b_range_ice	0.003***(0.000)	0.003***(0.000)	0.004***(0.000)	0.004***(0.000)
b_range_bev	0.001*(0.001)	0.001**(0.001)	0.003***(0.000)	0.003***(0.000)
Scale parameter				0.571***(0.039)
Socioeconomic variables				
Gender		0.310***(0.097)		-0.114 (0.155)
City size		0.172**(0.090)		-0.076 (0.048)
Garage charge		0.705***(0.100)		0.409***(0.156)
Income		-0.296(0.191)		-0.020 (0.245)
Model diagnostics statistics				
No. of individuals	794		794	
No. of observations	9528		9,528	
Adj. Rho-square (0)	0.195		0.197	
LL (0)	-17095.15		-17095.15	
LL (final)	-13739.71		-13698.55	
AIC	27511.41		27445.1	
BIC	27626		27616.99	

NOTE: a: tested with the value of 1; *Significance level at 10%; **Significance level at 5%; ***Significance level at 1%.
Legend: Gender: male = 1, female = 0; City size: rural = 1, medium/small size city = 2, large size city = 3; Garage charge availability: yes = 1, no = 0; Income: high (> €70,000) = 1; others = 0

7.3. MXL results

To capture the potential preference heterogeneity, we used the random parameters associated with the ASC_BEV, purchase price, and driving range in the MXL model. The random parameters were assumed to have been normally distributed for the ASC_BEV, purchase price, and driving range of ICEVs and BEVs, as in the studies of (Danielis et al. (2020); Scorrano and Danielis (2021c)). To obtain the best model with parameters, we used random parameters to capture the heterogeneity preference on BEVs. Then, we tested several specifications: random parameters with ASC_BEV, price and driving range, fixed parameters of ASC_BEV, and random parameters with purchase price and driving range. Finally, we chose the model with better fitness, assuming normally distributed parameters for ASC_BEV, purchase price (net), driving range of ICEVs and BEVs.

The results of the model with the best fitness are reported in Table 24. To identify the model, we set the price attribute to be generic and the other model parameters to be sample-specific. As expected, all the coefficients were significant. Since unobserved factors in the models might cause underlying variance, to compare the heterogeneity of the two samples, we introduced a scale parameter, which was the inverse of the standard deviation of the error items, to capture the variation of factor impacts which were not included in models (Hess & Train, 2017). We normalized the scale parameter to 1 for the Italian sample, after which we estimated the scale parameter of the Chinese sample by comparing it with that of the Italian sample. The value of the scale parameter was not insignificant from 1; hence, we cannot reject the null hypothesis (H0: $\lambda = 1$) that the unincluded variables can affect the estimated parameters through similar behaviors, confirming that the two samples had the same variance. All the estimated coefficients of the two countries significantly differed.

Petrol cars, *ceteris paribus*, are still considered reference cars. HEVs are strongly preferred to petrol cars in Italy. Although the share of petrol cars is declined in Chinese market, respondents still assign a high utility of petrol cars to other powertrains in China. The standard deviations of the preference for BEVs in both countries were highly significant, indicating a high level of preference heterogeneity for BEVs among our samples. The coefficient associated with BEVs was significantly negative, Italians have a lower utility of BEVs on the average level than Chinese respondents.

The attribute of driving range is also significant as expected and a high level of heterogeneity. Respondents are sensitive to driving range. The parameters of the standard deviations of the purchase price and the driving range were significant, signaling a high level of heterogeneity in the evaluation of price attribute and the driving range attribute in both samples. This finding on the valuation of price heterogeneous preference is broadly in line with the findings of (Danielis et al. (2020); Qian et al. (2019)). Thus, a lower purchase price and a longer driving range will give BEVs higher utility. These results are in line with the findings of Danielis et al. (2020), (Rotaris et al. (2020); Scorrano and Danielis (2021a), 2021b)). Compared with the Chinese respondents, the Italians were moderately range-sensitive. The possible explanation is related with the higher driving distances in Italian sample than that in China. Considering the role of socioeconomic characteristics on the choice of BEVs, we found that respondents from the two countries who owned a garage for charging, ceteris paribus, have higher utility for BEVs. This was improved in the Italian survey, as Danielis et al. (2020) found that garage ownership plays a positive role in EV preference, but the coefficient is insignificant. This is also consistent with the finding by Y. Huang and Qian (2018) of the high willingness to pay for home-charging infrastructure by the respondents in the Chinese market.

Finally, we tested the impact of the socioeconomic characteristics and found that only the garage charging availability significantly affected the purchase choices of BEVs in Italy while no significant sign among Chinese respondents. This might be explained by the driving range sensitivity in our Italian sample and the actual driving experience for Chinese respondents were limited. In both countries, we also tested the impacts of the other socioeconomic variables (gender, city size, net family income level per year) on the choices of BEVs, however, we have found that none of them played significant roles in both countries.

Table 24 Results of the MXL model

	MXL Models	
Vehicle and attributes	**Italy**	**China**
Asc_petrol	0	0
Asc_diesel	-0.242***(0.059)	-1.731***(0.142)
Asc_lpg	-0.528***(0.059)	\
Asc_cng	-1.678***(0.130)	\
Mu_Asc_bev	-6.583***(0.707)	-3.152***(0.382)
SD_Asc_bev	2.432***(0.223)	-2.475***(0.233)
Asc_hev	0.388***(0.064)	-0.044(0.053)
Asc_phev	-1.742***(0.137)	-0.638***(0.082)
b_price	-0.133***(0.009)	-0.133***(0.009)
SD_b_price	-0.188***(0.009)	-0.188***(0.009)
Mu_b_range_ice	0.004***(0.000)	0.002***(0.000)
SD_b_range_ice	-0.004***(0.000)	-0.003***(0.000)
Mu_b_range_bev	0.014***(0.001)	0.005***(0.001)
SD_b_range_bev	-0.001***(0.000)	-0.005***(0.001)
Scale parameter (λ)		0.895(0.063)
Socioeconomic variables		
Garage charging	1.128***(0.313)	0.433(0.311)
Income	-0.803(0.641)	-0.201(0.529)
Gender	0.178(0.323)	-0.031(0.312)
City size	0.414(0.281)	0.115(0.218)
Model diagnostics statistics		
No. of individuals	794	
No. of observations	9,528	
Adj. Rho-square	0.197	
LL (0)	-17095.15	
LL (final)	-13698.55	
AIC	27445.1	
BIC	27616.99	

NOTE: λ: *t*-test against 1; *Significant level at 10%; **Significant level at 5%; ***Significant level at 1%.

Legend: Gender: male = 1, female = 0; City size: rural = 1, medium/small size city = 2, large size city = 3; Garage charge availability: yes = 1, no = 0; Income: high (> €70,000) = 1; others = 0

7.4. **HMXL results**

7.4.1. **HMXL results of Italy**

Using the structural and measurement equations, we considered the latent variables influencing EV selection in the hybrid mixed choice model. The estimated results are listed in Table 25. The results of the HMXL model included three parts: the choice component, including socio-economic variables; latent variables, including structural and measurement parts; and model diagnostic statistics.

Petrol cars, *ceteris paribus*, are considered reference cars. With regard to ASCs, which capture the preferences of respondents for the different propulsion systems, the coefficient of BEVs is significantly negative, implying that the utility associated with BEVs is lower than that associated with the ICEV on average. For the attributes of purchase price and driving range, we used a random parameter to capture preferences in our samples. To be noticed, we have converted Chinese prices from the RMB to the Euro (€1 = 8) to have parameter comparability across the two countries[4]. For the purposes identified in the joint model, the attribute of purchase price is assumed to be generic between Italy and China, while the remaining parameters are sample-specific. The standard deviation coefficients on purchase price are significant, as expected; price heterogeneity exists between the two samples. Then we tested the socioeconomic characteristics of respondents on the price of BEVs and specified some interaction terms for socioeconomic variables (i.e., gender and income), but no significant relationships were found.The driving range coefficient of BEVs is significant positive, as expected; high heterogeneity was observed in both countries, with Italians being more range sensitive.With reference to the driving range of BEVs, the coefficient of ICEV range is much lower; this is in line with previous findings by Giansoldati, Rotaris, et al. (2020).

Garage charging availability is significantly positive in both countries for socio-demographic characteristics, indicating that a respondent who has owned a garage for charging availability would have a high utility of BEVs. This is improved in the Italian survey, as Danielis et al. (2020) discovered that garage ownership has a positive effect on EV ownership, but the coefficient is not significant. Specifically, Chinese respondents are more sensitive in this aspect. The possible explanation might relate to the low proportion of private garage ownership in our Chinese samples. This is also consistent with the finding by Y. Huang and Qian (2018), who confirmed a high willingness to pay for home charging infrastructure among respondents in China.

According to the factor analysis results, we got the estimated results of structural and measurement equations for latent variables. LV1 is labeled as “Not

[4] The currency is based on the period when we have carried out our survey between 2021 and 2022. Although the currency rate has changed at this stage, we have decided to keep the rate consistent with the period of previous data collection.

skeptical about EVs", which includes the indicator Q3 (It is not practical to drive an electric car because of the infrequent charging points), Q8 (Long time required for charging an electric car makes the use of electric cars unpractical), Q9 (Using an electric car requires careful travel planning) and Q16 (Limited driving range would make/makes me feel uncomfortable to drive an electric car). From the utility function, the coefficient of $\lambda_{charging}$ is significantly positive, indicating that those who are "Not skeptical about EVs" are more likely to place a high utility on BEVs. The parameters of the measurement equation (τ) on LV1 are all significantly negative. High values of the indicators correspond to respondents who are skeptical about EVs. More specifically, respondents with higher levels of "Not skeptical about EVs" are less likely to agree with the attitude of Q3 ("It is not practical to drive an electric car because of the infrequent charging points"), Q8 ("Long time required for charging an electric car makes the use of electric cars unpractical"), Q9 ("Using an electric car requires careful travel planning"), Q16 ("Limited driving range would make me feel uncomfortable to drive an electric car"). For the structural equations, respondents who have a garage for charging are more likely to choose EVs.

The latent variable LV2, labeled as "Late adopters", includes the indicators of Q1 ("The purchase price is still too high. I prefer to wait") and Q13 ("I think the purchasing subsidy for buying an electric car is currently too low"). From the utility function, the coefficients of $\lambda_{economic}$ is significantly positive as expected, implying respondents who are "Late adopters" have a high utility on BEVs. The indicator of τ_Q13 is significantly positive. Higher values of the indicator imply the respondents are more likely to be "Late adopters". According to the structural equation, respondents with high-income levels are more likely to choose EVs at the current stage.

The latent variable LV3 labeled as "EVs are not environmentally friendly", measured by indicators of Q6 "Driving an electric car is a more environmental friendly way of transportation than driving a conventional car" and Q7 "I am not convinced that electric cars pollute less than conventional cars due to battery disposal". In order to keep consistency effects between two statements on the factor group, we have reversed Q7, naming the indicator Q7A, to make sure the ones that are given high scores match low scores with Q6, and then Q7A is reversed as "I am convinced that electric cars pollute less than conventional cars due to battery disposal". From the utility function, the coefficients of $\lambda_{environment}$ is significantly negative, indicating that respondents who are concerned with "EVs are not environmentally friendly" have lower utility on BEVs. The coefficients of indicators τ are significantly negative. High values are consistent with high environmental awareness. In particular, individuals with high levels of "Not Concerned about the environment" are less likely to agree with Q6 "Driving an electric car is a more environmental friendly way of transportation than driving a conventional car" while they are more likely to agree with Q7A "I am convinced that electric cars pollute less than conventional cars due to battery disposal". For the structural equation, women were more likely to show environmentally aware on EVs.

The latent variable LV4, named as "EVs are fast, safe and fun to drive", is measured by the indicators Q10 "I think the performance of an electric car is inferior to the performance of a conventional car", Q12 "I would not feel safe driving an electric car given the large size of the battery and considering the risk of fire" and Q15 "I would enjoy driving an electric car more than driving a conventional car". We reversed Q15 to make sure the high-scoring answers corresponded with the low-scoring answers of Q10 and Q12. Then Q15A is named as "I would not enjoy driving an electric car more than driving a conventional car". According to the utility function, the coefficients of $\lambda_{driving}$ are significantly positive, indicating that individuals who agree with "EVs are fast, safe and fun to drive" have a high utility on BEVs. The indicators are significantly negative, as expected. Higher values of the indicators Q10, Q12, and Q15A indicate respondents are skeptical. For the structural equation, male respondents and people with a larger number of cars are more likely to choose BEVs.

7.4.2. **HMXL results of China**

The results of China sample are listed in Table 26. The diagnostic statistics index indicates the fitness of our model is good. For the Chinese sample, gasoline cars are still considered reference cars. The coefficients for diesel, PHEV, and BEV are negative, implying lower utility for Chinese respondents, particularly in terms of BEVs. Specifically, we used random parameters to capture heterogeneity preferences for BEVs; the coefficients of standard deviation on BEVs are significant, indicating that heterogeneity preferences for BEVs exist in our Chinese sample. The mean value of BEVs is significantly negative, reflecting that respondents are less likely to choose BEVs on average.

For the attributes of purchase price and driving range, the coefficients of standard deviation on purchase price and driving range of BEVs are significant showing heterogeneity preference exists; the coefficient of mean value of purchase price is negative, indicating heterogeneity preference can be captured with an average level, and high purchase price will cause low utility of BEVs. The coefficient of mean value of driving range is highly positive, indicating that consumers have a high average utility for BEVs if the driving range improves. For the socio-demographic characteristics, garage charging availability is significantly positive, indicating that people who have a garage where a BEV can be charged are more likely to choose a BEV.

The latent variable LV1 in China, in order to be consistent with the label of the Italian sample, is still given the label "skeptical about EVs", including the indicators Q3 (It is not practical to drive an electric car because of the infrequent charging points), Q4 (The construction of a domestic charging infrastructure is a bureaucratically complicated and expensive process, especially in an apartment), Q5

(The electric car poses a problem of where to charge and at what cost, especially for those who do not own a garage), Q8 (Long time required for charging an electric car makes the use of electric cars unpractical), Q9 (Using an electric car requires careful travel planning) and Q16 (Limited driving range would make/makes me feel uncomfortable to drive an electric car). From the utility function, the coefficients of $\lambda_{charging}$ are significantly positive, indicating that the respondents who are "Not skeptical about EVs" are more likely to have a high utility on BEVs. The parameters of the measurement equation (τ) on LV1 are all significantly negative. High values of the indicators correspond to respondents who are skeptical on EVs. More specifically, respondents with higher levels on "Not skeptical about EVs" are less likely to agree with the attitude of Q3 ("It is not practical to drive an electric car because of the infrequent charging points"), Q8 (Long time required for charging an electric car makes the use of electric cars unpractical"), Q9 (Using an electric car requires careful travel planning") and Q16 ("Limited driving range would make me feel uncomfortable to drive an electric car"). For the structural equations, respondents who have a garage for charging are more likely to choose EVs.

The latent variable LV2 is labeled as "Late adopters", including the indicators of Q1 ("The purchase price is still too high. I prefer to wait"), Q13 ("I think the purchasing subsidy for buying an electric car is currently too low") and Q14 ("I think the number of free parking hours granted for electric cars enacted by some municipalities is too low"). As expected, the coefficients of $\lambda_{economic}$ is significantly positive, indicating that respondents who are "Late adopters" show high preference on BEVs. All the indicators in China are significantly positive. Higher values of the indicators imply the respondents who are more in agreement with the attitudes are more likely to become "Late adopters". According to the structural equation, the socio-economic characteristics of household income level are statistically significant, indicating that income is not a sensitive factor for our Chinese sample.

The latent variable LV3, labeled as "EVs are fast, safe and fun to drive" is measured by the indicators Q10 "I think the performance of an electric car is inferior than the performance of a conventional car" and Q12 "I would not feel safe driving an electric car given the large size of the battery and considering the risk of fire". From the utility function, the coefficient of $\lambda_{driving}$ is highly positive, indicating that individuals who agree with the statement "EVs are fast, safe and fun to drive" place a high utility on BEVs. The indicator of τ is significantly negative as expected. Higher values of the indicators indicate that respondents are skeptical about the fast, safe and fun performance of EVs. According to the structural equation, car-owning individuals are more inclined to prefer BEVs.

Table 25 HMXL model results in Italy

Part A: Vehicles, price and driving range attributes	
Asc_diesel	-0.200***(0.063)
Asc_lpg	-0.507***(0.060)
Asc_cng	-1.570***(0.131)
Asc_hev	0.447***(0.066)
Asc_phev	-1.535***(0.146)
Asc_bev	-4.952***(0.602)
Price(BEV)	-0.155***(0.011)
SD_Price(BEV)	-0.171***(0.008)
Range_ICE	0.004***(0.000)
SD_Range_ICE	0.004***(0.000)
Range_BEV	0.013***(0.001)
SD_Range_BEV	0.002***(0.000)
Socio-economic variables	
b_garagecharging	0.386***(0.125)
Part B: Latent variables	
LV1: Not skeptical on EVs	
$\lambda_{charging}$	0.694***(0.170)
Measurement equation for LV1	
τ Q3	-1.316***(0.154)
τ Q8	-2.320***(0.265)
τ Q9	-1.538***(0.173)
τ Q16	-1.857***(0.201)
Structural equation for LV1	
γ_garagecharging	0.373***(0.055)
LV2: Late adopters	
$\lambda_{economic}$	1.466***(0.135)
Measurement equation for LV2	
τ Q1	0.100
τ Q13	0.347***(0.119)
Structural equation for LV2	
γ_income	-0.244*(0.151)
LV3: EVs are not environmentally friendly	
$\lambda_{environment}$	-0.562***(0.179)
Measurement equation for LV3	
τ Q6	-2.249***(0.376)
τ Q7A	-1.629***(0.219)
Structural equation for LV3	
γ_gender	0.306***(0.094)
LV4: EVs are fast, safe and fun to drive	
$\lambda_{driving}$	0.688***(0.208)
Measurement equation for LV4	
τ Q10	-1.014***(0.168)
τ Q12	-0.913***(0.154)
τ Q15A	-0.740***(0.150)
Structural equation for LV4	
γ_gender	0.599***(0.142)
γ_carownership	0.187***(0.000)
Part C: Diagnostics statistics	
Number of individuals	436
Number of rows in database	5232
Number of modelled outcomes	10028
LL(start)	-18355.52
LL(final)	-12849.45

AIC	25858.89
BIC	26435.94

Note: ***, **, * indicate significance at 1%, 5% and 10% level respectively

Table 26 HMXL model results in China

Part A: Vehicles, price and driving range attributes	
Asc_ diesel	-1.551***(0.068)
Asc_hev	-0.034
Asc_phev	-0.577***(0.059)
Asc_bev	-2.227***(0.364)
Price(BEV)	-0.016***(0.000)
SD_ price(BEV)	-0.025***(0.001)
Range_ice	0.001***(0.000)
SD_range_ice	0.003***(0.000)
Range_bev	0.005***(0.001)
SD_range_bev	0.004***(0.000)
Socio-economic variables	
Garagecharge	0.723***(0.201)
Part B: Latent variables	
LV1: Not skeptical on EVs	
$\lambda_{charging}$	0.641**(0.272)
Measurement equation for LV1	
τ Q3	-1.599***(0.193)
τ Q8	-1.464***(0.178)
τ Q9	-1.243***(0.175)
τ Q16	-1.253***(0.170)
τ Q4	-2.274***(0.296)
τ Q5	-1.549***(0.203)
Structural equation for LV1	
γ_garagecharging	0.329***(0.079)
LV2: Late adopters	
$\lambda_{economic}$	0.661***(0.229)
Measurement equation for LV2	
τ Q1	3.549***(0.301)
τ Q13	1.715***(0.322)
τ Q14	1.478***(0.252)
Structural equation for LV2	
γ_income	-0.052(0.083)
LV3: EVs are fast, safe and fun to drive	
$\lambda_{driving}$	2.025***(0.132)
Measurement equation for LV3	
τ Q10	-0.255**(0.105)
τ Q12	-0.175*(0.108)
Structural equation for LV3	
γ_gender	0.149
γ_carownership	0.217**(0.100)
Part C: Diagnostics statistics	
Number of individuals	358
Number of rows in database	4296
Number of modelled outcomes	8234
LL(start)	-13412.78
LL(final)	-10445.4
AIC	21040.81
BIC	21567.01

Note: ***, **, * indicate significance at 1%, 5% and 10% level respectively

7.5. **Conclusion**

This chapter explores the econometric results of three models implementation: MNL, MXL, and HMXL. The analysis of the MNL model confirms that respondents in both countries have higher utility on BEVs than on ICEVs. For the vehicle attributes, all attributes are significant and have the expected signs. The purchase price and driving range are both significant for the utility of BEVs, which is also in line with the reviewed studies. Regarding socio-economic interaction, garage charging availability for BEVs plays a significantly positive role in Italy and China. Moreover, men are more likely to choose BEVs than women for the Italian sample, and a lower purchase price would cause higher utility. People living in large cities and those who live closer to their workplaces also place a high utility on BEVs. In addition, people who have a high household income are more likely to choose BEVs in China.

The estimation analysis performed with MXL confirmed that the financial attribute (purchase price) and non-financial attribute (driving range) are significant in both countries as expected. The standard deviation of prices and range in both countries is highly significant, indicating heterogeneity preference exists in our samples. However, if governments in both countries need to encourage the adoption of BEVs, policy incentives such as increasing the total cost of ownership (TCO) reductions in Italy and reducing annual operating costs in China are more effective (Qian et al., 2019; Scorrano et al., 2020). The main differences of our findings in comparison with previous studies are that Italians are more sensitive to the driving range than the Chinese, given that the coefficient value of the driving range is higher in the Italian sample, in contrast with the opposite finding in Danielis et al. (2020), Rotaris et al. (2020) and Giansoldati, Monte, et al. (2020). This also indicates that the driving range issue still needs to be solved on the uptake of BEVs in the Italian market. Although China has a larger geographical size, the garage charging availability is more sensitive for Italian respondents than for Chinese ones. Some possible reasons are that more than 50% of Chinese respondents do not drive a car every day, which causes less sensitivity to the recharge time related to the car battery.

The hybrid model specification is better at explaining the choice process. We have tested the latent variables and given labels as: “Not skeptical about EVs”, “Late adopter”, “Not an environmental friendly way”, and “EVs are fast, safe and fun to drive” in the two countries. We have found that all the latent variables are significant both in Italy and China, except for the latent variable of “Not environmental friendly way for EVs”, which is not significant in China. Specifically, environmental awareness has a statistically significant positive impact on the choice of BEVs in Italy. This is also confirmed in the previous studies (Danielis et al., 2020; Rotaris et al., 2020), sespecially for respondents with higher levels of awareness about global environmental issues, who are more likely to have participated in an environmental event (Scorrano & Danielis, 2021a). Considering our socio-economic characteristics, women who with environmental awarenessare are more likely to choose EVs, and respondents with a high income level and people who own more cars are more likely to choose EVs.

8. Model Application

8.1. Introduction

Our estimated model can be used to assess the impact on the customer choices of policy incentives and technological progress on EVs. In this chapter, we have simulated the choice probability based on the estimated parameters of MXL results. In section 8.2, we have described the application scenarios, including financial incentives (price reduction), technology improvement (range increased), and multiple incentives, and finally got the results (section 8.3).

8.2. Application description

Two market-oriented instruments were implemented to estimate the impacts of financial incentives and technological improvement on the probability of choosing BEVs compared to the probability of ICEVs. We calculated all vehicles' probabilities, using the econometric results in MXL model. We considered three hypothetical scenarios to evaluate the potential changes in the market share of BEVs. The simulated scenarios are as follows.

Scenario 1: Reduce the purchase price by 20%.

Scenario 2: Increase the EV driving range by 50%.

Scenario 3: Combine Scenarios 1 and 2.

Scenario 1 is inspired by the government policies in both two countries. Purchase subsidies have been introduced by the Italian government since 2019, which are up to €8,000, with the CO_2 emissions of a new car lower than 290 g/km in 2021. The recent study carried out by Rotaris and Danielis (2019) confirmed the Italians willingness to pay between €0.17 and €0.30 per liter for reducing CO2. However, in the Chinese market, purchase subsidies are being reduced each year because of massive redundant financial expenditures (L. Li et al., 2022). Therefore, we decided to use price reduction as an attribute with a changing level in both countries. Scenario 2 is inspired by the new technological improvement in the realistic market, which reflects that the average range of EVs is increasing constantly until it reaches an average range of around 280 km (Nykvist et al., 2019). A similar scenario was used in recent studies to test the probability of changing EVs in the Italian market (e.g., Danielis et al. (2020)). Scenario 3 considered all attribute changes simultaneously on BEVs. The incentive policy details in the two countries are listed in Table 27 and Table 28.

Table 27 Italy "Ecobonus" in 2021

CO2 BAND g / km	Scrap Incentive	Incentive without scrapping	Price Limit
0-20	€ 8,000 (+ € 2,000 contribution from the concessionaire)	5,000 euros (+1,000 contribution from the concessionaire)	€ 50,000
21-60	4,500 euros (+2,000 contribution from the concessionaire)	2,500 euros (+1,000 contribution from the concessionaire)	€ 50,000
61-135 g / km (until June 2021)	1,500 euros (+2,000 contribution from the concessionaire)	0 euro	€ 40,000

Note: Summarized from ACEA (Italy)

Table 28 China policy incentives in 2021 (passenger cars market)

Type	Driving range R (km)		
BEV	300 ≤ R <400	R ≥ 400	R >=50
	¥13,000	¥18,000	/
PHEV (include Extended Range Electric Vehicle)	/		¥ 6,800*

Note: Summarized from the official files of China State Council

*For the currency, we converted the RMB to the Euro (€1=¥8) to maintain parameter comparability across the two countries

8.3. Application results

First, we estimated the probabilities using a baseline scenario, which included the net price with no subsidies and the current driving range. The baseline estimation in Italy was higher on average than that in the real market in 2021 (6% vs. 4.6%, respectively). The explanation might be related to the data we used (i.e., the SP data) instead of the RP data in our application. The baseline estimation in China is lower than that in the real market in 2021 (7% vs. 13%, respectively). However, compared with the scenario where no instruments were implemented, all the policy instruments in our scenarios were seen as promoting the probability of consumers choosing to purchase a BEV.

In Scenario 1, the market share of BEVs in Italy can slightly increase to 7% compared with the baseline scenario. In fact, Danielis et al. (2020) have already confirmed the EVs uptake is benefit from the financial policies. However, although the market share of BEVs in China has increased to 8%, the simulated market share of BEVs is still lower than that in the actual market in 2021, where petrol cars are still the mainstream.

Scenario 2 shows that a 50% higher driving range would increase the probability of the purchase of BEVs in Italy to 15%, which is higher than the one in the current real market. The application result is in line with our econometric results, which showed that Italians are range-sensitive. In recent researches, Nykvist et al. (2019) confirmed that EV drivers became free of range anxiety when the driving range of EVs increased constantly. This might explain the increased probability of choosing EVs with a 50% increased driving range in Italy. However, although the probability in China increased to 10%, it is still lower than the probability in the real market in 2021. This might be related with the Chinese market share of BEVs is influenced by the other factors, such as the requirement for consumer to obtain a vehicle license immediately (Qian et al., 2019).

When we combined the two scenarios, the total probability in both countries slightly increased, which implies that if Scenario 3 is realized, the uptake of EVs in the Italian market would increase. Surprisingly, however, the probability in the Chinese market was still lower than the real market share, more reasons should be further explored in Chinese market, such as home-charging capability which was confirmed as the significant factor on the adoption of EVs (Qian et al., 2019). All the simulated probabilities are listed in Table 29.

Table 29 Predicted demand at model estimates

	Italy (% of simulated market share)				China (%of simulated market share)			
	Baseline	**Scenario 1**	**Scenario 2**	**Scenario 3**	**Baseline**	**Scenario 1**	**Scenario 2**	**Scenario 3**
Petrol	17	16	14	13	14	13	13	12
Diesel	12	12	10	10	5	5	5	5
LPG	6	6	5	5	\	\	\	\
CNG	1	1	1	1	\	\	\	\
BEV	**6**	**7**	**15**	**16**	**7**	**8**	**10**	**12**
HEV	11	11	9	9	13	13	12	12
PHEV	2	2	1	1	5	5	5	5

8.4. **Conclusion**

We have conducted a model application on the critical attributes of the purchase price and driving range. We have assumed three scenarios to simulate how the probability of buying EVs changes with single or multiple policy incentives.

Several findings are found in our simulation analysis. First, compared with no incentives, all the policy incentives are effective in promoting the uptake of EVs. Second, multiple price and range policies are more effective than a single policy in EVs markets in both countreis. Third, compared with Chinese sample, Italian respondents are more cost sensitive and more dependent on the financial benefits. Fourth, for Chinese samples, technological advancements and increased range are more significant; this is consistent with the findings of L. Li et al. (2020), which investigated technology improvement has great impact on the probability of choosing BEV.

It is worth noting that the simulations is just compared the effects of purchase price and driving range on the probability of choosing BEVs, rather than forecasting the market shares of BEVs in both two countries. More factors should be considered when the policies are implemented. In addition, customer choices and different alternatives availability might change over time, which might also change the effect of policy implementation on the preference for EVs.

9. Agent-Based Model in EVs Market

9.1. Introduction

This chapter employed an agent-based model (ABM) to simulate the potential adoption of EVs in Italy and China to identify how policy instruments simulate the diffusion of EVs. In section 9.2, we provided a detailed review of ABM on the car market, and then developed the ABM in both Italy and China markets up to 2030 (section 9.3). Following that, we have present the simulation results and conclusions (section 9.4 and 9.5).

9.2. Related literature review

9.2.1. Overview of Agent-based model (ABM)

Three dimensions are used to describe car market research methodologies: top-down models, bottom-up models, and hybrid models (Jochem, Gómez Vilchez, Ensslen, Schäuble, & Fichtner, 2018). The top-down model relies on historical consumption data, including prices, income, and factor costs, to apply macroeconomic theories, econometrics, and optimization techniques to aggregate economic variables by considering all main economic sectors. Bottom-up models are based on simulation techniques to reflect heterogeneous characteristics of socio-economic activity calibrated with disaggregated data. Mundaca, Neij, Worrell, and McNeil (2010) have identified four principal methodologies to build bottom-up models: simulation, optimization, accounting, and hybrid. They discovered that agent-based modeling can explore varied preferences represented with individual adoption (Hesselink & Chappin, 2019). Zhuge, Wei, Shao, Dong, et al. (2020) have summarized the commonly used modeling to explore the impact of incentives on EVs adoption: discrete choice models, regression models, and agent-based models.

An agent-based model (ABM) is an innovative way to use computer science to simulate the diffusion of agent interaction in a socioeconomic system (Squazzoni, 2010). More precisely, ABM is a specific computational method that allows researchers to create, analyze and build models in an interactive environment. Multiple participants are integrated into an object-based architecture that investigates the effect of market penetration on market share. ABM can explicitly simulate the dynamics of social interaction processes and individual behaviors by considering the heterogeneity of customers. The reviewed studies are summarized in Table 30. The recent studies of ABM are divided into two streams: theoretical insights, which are concerned with the diffusion process, and practical application, which emphasizes empirical data (Kiesling, Günther, Stummer, & Wakolbinger, 2012). Recent studies have combined two streams into transportation markets and developed models with influenced factors in vehicle research. Wolf, Schröder, Neumann, and de Haan (2015) used an agent-based model with artificial neural networks and confirmed the role of emotions in the informed decision-making process. Jochem et al. (2018) have investigated the heterogeneity of car purchases and confirmed that individual preferences influenced car penetration; this is also investigated in the study of Oliveira, Roth, and Dias (2019). Moreover, Macal (2016) listed five conditions used in ABM modeling: distributed systems, interacting agents, defined decisions, behaviors to reflect system operation, and adaptation within the system by entities changed, which can affect the nature of systems.

Consumers are the core agent type in the agent-based model. One of the most widely used approaches to simulating customer behavior in the EV market is utility maximization theory. Different attributes, such as vehicle costs, technology maturity, eco-friendship, and social influence, were used as the parameters to calculate the utility of agents (Adepetu & Keshav, 2017; Buchmann, Wolf, & Fidaschek, 2021; Gnann, Plötz, & Wietschel, 2019; W. Yang, Xiang, Liu, & Gu, 2017; 2015). Ahkamiraad and Wang (2018) have also explored the role of word of mouth and considered the iteration among different zip-code areas. Zhuge, Wei, Dong, Shao, and Shan (2019) have conducted more research on the utility of daily plans and the environment based on the activity-based travel demand model.

Furthermore, some studies have applied ABM modeling to transport fields (Hesselink & Chappin, 2019; Le Pira et al., 2017; Sun, Liu, Wang, & Yuan, 2019; W. Yang et al., 2017). They used ABM to build patterns and generate results by mixing actual world data with behavior theories to simulate consumer behavior and evaluate the efficacy of transportation policies. Noori and Tatari (2016) have deeply developed ABM in conjunction with exploratory modeling and analysis (EMA) method to examine the penetration of EVs. Kangur, Jager, Verbrugge, and Bockarjova (2017) used personal preferences and the other two behavior-driving forces: existence/sustainability and social belonging/status, in their research. Klein, Lüpke, and Günther (2020a) have considered individual possibilities of home charging in agent-based simulation and revealed that technological progress in charging time could increase the market share of PHEV. Zhuge et al. (2019) have emphasized the environment, power grid system, and urban infrastructures as dynamic expansion factors in the EV market expedition. Moreover, Hesselink and Chappin (2019) have examined the ABM studies related to technologies and discovered that ABMs can explore dichotomous adoption decisions to stimulate multiple competitive technologies improvement.

Some other studies paid more attention to individual neural networks, considering maximizing satisfaction of constraints resulting from individual mental and psychological representations. Kangur et al. (2017) developed psychological customer modeling and paid their attention on information methods for complicated behavior rules regarding the effects of attitudes and behavior in the process of electric car markets. Ning, Guo, Liu, and Pan (2020) have developed a choice behavior diffusion model based on social network theory and total utility theory and investigated individuals' preference heterogeneity.

However, although an agent-based model can capture temporal and spatial effects to reflect consumer heterogeneity as well as social influence in diffusion events (Klein et al., 2020a), they lack an empirical foundation to reflect actual market behavior. Even though ABM parameters are derived from socio-demographic data sets, the actual choices of individuals are not accurately reflected. Researchers have used an agent-based model with a stated preference survey and constructed hypothesized scenarios to overcome the uncertainty reflected in the revealed preference data.

9.2.2. **Modeling approaches**

The ABM can forecast the market penetration of alternative vehicles in the passenger car market through a series of possible actions that might affect the simulation process. Two methods have been used in previous studies: created synthetic agents according to the population characteristics and replicated respondents as agents (Brown, 2013). The modeling structure on vehicle technologies can perform in two ways: discrete choice (DC) structure and discrete choice structure constructed with additional processes (Vilchez & Jochem, 2019).

Discrete choice modeling is used to evaluate vehicle choice and features (Jochem et al., 2018). The representation of car stock is critical , and it can be generally formulated with age , size or the other multiple levels of disaggregation (Vilchez & Jochem, 2019). The fundamental concept is to simulate customer behavior and estimate the valuation of vehicle attributes. They are frequently used with random utility models (RUMs). The assessment of each product gained from expressing preference surveys is employed as an output; each attribute describing the qualities of the product is deconstructed into individual utilities, and then the part-worth utility of all attributes is added together to determine the total utility. Querini and Benetto (2014) have compared the random choice model to the structural model by using the simulated number in their scenarios to improve structure models on the development of alternative vehicles. Thies, Kieckhäfer, and Spengler (2016) have used the estimated results of the multinomial logit (MNL) model to simulate the compatitive long-range passenger cars. Palmer, Sorda, and Madlener (2015) summarized four partial weighted utilities and compared the utility of potential adopters with a threshold level. Moreover, socio-norms in individuals' utility were also highlighted in recent studies. Brown (2013) has developed a mixed logit choice model (MXL) with social network interactions to evaluate social actors and behaviors. To confirm the heterogeneous vehicle attributes, researchers choose to use a mixed logit model and conduct simulations within an agent-based framework (Train, 2009). Noori and Tatari (2016) employed econometric models using disaggregated data to evaluate the possible outcomes and confirmed the trend of data-driven hybrid approaches in EV market penetration studies. Ensslen, Will, and Jochem (2019) have used a binary logistic regression model to assess adoption possibilities on the energy system by examing the the dependencies between intentions of PEV adoption and socio-economic variables.

Choice-based conjoint analysis (CBC), the most widely applied form of conjoint analysis, is usually carried out to examine individual preferences in simulation studies. Researchers employ the algorithms of Monte Carlo analysis as a decision-making tool to estimate the action risks. In choice-based conjoint analysis (CBC), respondents are asked to deal with a large amount of information in choice tasks. They are asked to choose the products according to given choice tasks which can represent the preferences of the objects (Klein et al., 2020a). However, estimation and application studies use distinct discrete choice structure assumptionsv(Vilchez & Jochem, 2019). The assumption in estimating studies is performed by explicit parameters in utility functions derived from a survey of stated and revealed preference. Other application studies can use the findings of estimated research into their system model. In system dynamic models, these numerical assumptions are investigated through sensitivity analysis, which is commonly accomplished by Monte Carlo simulation employing probability distributions (Kleijnen, 1995).

Combing modeling techniques with econometric methods, researchers used empirical data from surveys to parameterize and initialize consumer behaviors for population features to predict market penetration. However, there are no standard languages for ABM modeling. The main structure is dependent on software to create using graphical editors or scripts (Borshchev, 2013). Many Java software was implemented in related studies, including NetLogo, InnoMind, JADE, Repast Simphony, MATLAB, MATSim, and Anylogic. Although agent-based approaches can explain effects on consumer heterogeneity or social influence, they often need an empirical foundation and adequately reflect actual behavior in fundamental markets.

9.2.3. **Summarized**

As reviewed in previous studies, many factors, including monetary or technology factors, have been mentioned in the promotion of the EVs market, and financial attributes were generally confirmed as significant factors in the utility of EVs. However, researchers paid more attention to the assessment of implication policy on EVs uptake and neglected the further penetration of the EVs market. In our paper, we have attempted to assess the diffusion of EVs with policy implications in a dynamic way.

The system dynamics model, discrete choice model, and regression model are widely used in recent studies to assess the policy implications in the EVs market (Zhuge, Wei, Shao, Shan, & Dong, 2020). As the discrete choice model emphasizes the statistical relationships, neglecting the influence of complex networks (J. Li, Jiao, & Tang, 2020), in our paper, we will use ABM to capture car choice determinants and heterogeneity of decision-makers. We have integrated a simulation model with a discrete choice modeling technique, accounting for the socio-economic characteristics of the evolution of the EVs market and simulated customer behavior. The paper is expected to fully understand the influence of policy implementation on the diffusion of EVs from a spatial perspective.

Table 30 Summarized literature review on Agent-based model

Author(s)	Country	Vehicle types	Model type	Simulation period	Lauguage	Influenced factors	Findings
Wolf et al. (2015)	Germany	EVs	ABM, InnoMind (Innovation diffusion driven by changing Minds)	20 years (100 time)	Java	Psycholigical:emotion	Non-finiancial policy of exclusive zone for EVs is more effective in the early stage; Consumer group of bicycles is easily to change transportation mode.
Cho and Blommestein (2015)	USA	EVs	ABS model (Agent-based simulation model)	15 years	Netlogo	Incentives, Fuel price, EV price	The price preference is highly weighted for agents to adopt EVs; Low price for EVs and high gas price is easily influenced households decision.
W. Yang et al. (2015)	China	EVs	System Dynamics Model, Agent Based Model	30 years	JADE	Relative cost of the vehicle, Technique maturity, Eco-friendship, Social influence, Driving patterns of consumer, Availability of charging facilities, Charging price	Low technology and insufficient infrastructure in eartly stage would restrict EVs, Government policy is the main factor to promote EV
Noori and Tatari (2016)	USA	EREV(Gasoline Extended Range Electric Vehicle),BEV,HEV,PHEV	Electric Vehicle Regional Optimizer (EVRO), Exploratory modeling and analysis(EMA), (ABM)	2015-2030	Anylogic	Maintenance and Refueling (M&R) Cost, Environmental Damage Cost (EDC), Water Footprint (WFP)	BEVs are the most cost-effective vehicles, lowest enviornment damage cost, largest used water on average; ICEV is the highest maintenance and repair (M&R) cost; Government subsidies, Social acceptability and the word-of-mouth effect have

							significant effect on adoption of EVs; Rregional subsidy policy can increase social acceptability of EV.
Silvia and Krause (2016)	USA	BEV	ABM	Until 2030	NetLogo	Current vehicle age, BEV monthly payment, Driving range, BEV cost,Technologe innovate	Increase charging network cannot effect EV adoption;Vehicle visibility increased by gorvernment fleets and incentives on purchase price have moderate impacts; Hybrid policy is the most effctable on BEV
Kieckhäfer, Wachter, and Spengler (2017)	Germany	BEVs,FCEVs, PHEVs,HEVs	AMaSi model (automotive market simulator)	2010-2030	AnyLogic	Purchase decision, Manufacturer behavior and technology development, Infrastructure	Product portfolio for manufactures is more effective on EVs market; Purchase subsidy and infrastructure creation is effceted to increase sales of Evs; Profound mandate is very useful in market mechanisms; Hybrid EVs are very important to postitively influnce consumers' attitude to accept BEVs.
Kangur et al. (2017)	Netherla nds	PHEV,BEV,F uel	STECCAR model (Simulating the Transition to Electric Cars using the Consumat Agent Rationale)	July 2012 - July 2025	Repast Simphony 2.1	Market stability, Ownership aspects, Scrappage characteristics, Diffusion of electric vehicles.	TH ecar tax policies soly wrked on BEVs can significantly reduce carbon emission; Combined policy with rise in fuel costs or decrease in fast charge electricity costs could be more effctive on Evs; financial policies on EVs would stimulate PHEV adoption; Fast charge network positively influences BEVs adoption but no

							significant influence on PHEV
Adepetu and Keshav (2017)	USA	BEV,PHEV,HEV	Agent-based ecosystem model	5 years	MapQuest Route Matrix API	Electrical effiiency, Battery capacity, Electric range, Rebate, Purchase price	High battery capacity increase EV adoption slightly; EV rebater is significant increased adoption; Cost-competitiveness is more significant factor.
W. Yang et al. (2017)	China	PEV	ABM with scale evolution model	30 years	JADE	Economy, Social, Environment, Charging strategies	The scale of PEVs grows slowly in early stage; Incentive policy is vital to cultivate the initial market; Social dynamics would exacerbate the market inertia; Charging demand is the factor to influence evolution of PEVs
Jochem et al. (2018)	Germany	EVs	Hybrid Models	\	\	\	No common defination on ABM; Normally extend ABM model with other methods.
Ahkamiraad and Wang (2018)	USA	BEV, PHEV	ABM with threshold model (Fisher and Pry's diffusion model and Rogers model)	2016-2050	GIS	Median home values, Land area, Use of car/ truck/van,	Zip-code level grid infrastructure is influenced by the diffusion of EVs
Ensslen, Will, and Jochem (2019)	France, Germany	PEVs (plug-in electric vehicle)	Hybrid model, Bass diffusion model	Until 2030	\	Innovation,Charging behavior	Higher dynamics in France are likely the Stronger incentive for low-emitting vehicles and lower power prices are more effctive inFrance; Charging power on electric mileage has a higher effect in Germany; Battery capacity effect total energy flexible charging.
T. Gnann, Plötz, and Wietschel (2019)	Germany	PHEV	Agent-based simulation model Alternative Automobiles Diffusion and Infrastructure (ALADIN)	2015-2030	\	Subsidies on charging point, Charging power, Charging availability with additional	Heavy subsidized on public charging points is necessary until 2030; PEV diffusion is not affected by public slow charging points.

						charging at work, Limitation to recharge for individuals	
Oliveira et al. (2019)	Portugal	AFV	System Dynamics (SD), ABM, Choice Based Conjoint Analysis	2013-2052	\	Engine price, Range, Fuel/Electricity cost, CO2 emissions	Higher purchase incentives can promote AFV when customers are not familiar with them; Type of engine is significant on accelerating AFV
X. Sun et al. (2019)	China	EVs	ABM	2010-2050	MATLAB	Driving performance, Sales price, Post-adoption expenditure, range, Total cost of ownership, Subsidy	Consumer subsidy is more effective than manufacturer subsidy; Subsidy intensity and duration are more effective on policy
Zhuge et al. (2019)	China	BEV, PHEV	Agent-based integrated urban model (SelfSim-EV), Activity-based travel demand model (MATSim-EV), Multinomial logit model	2016-2020	MATSim	ABM: Environment, Power grid system, Transport infrastructures, Utility: Social influence, Driving experience, Purchase price	Vehicle purchase permits can increase BEV sale; Neighbour effects can influence BEV adoption; Enviornment is significant on BEV diffusion; Private charging faclities are more effective than public charging.
Klein et al. (2020)	Germany	PHEV,EV	Agent-based simulation model (ABS), Choice-based conjoint study (CBC)	50 times	AnyLogic	Consumption costs, Range, Station charging time, Engine type, Home charging possibility, Station density, Price.	Homing charging has an important influence but with decreased importance because of faster charging time with public charging station; Technology improvement can cannibalize the market share of PHEV,but government subsidy can promote PHEV
Ning, Guo, Liu, and Pan (2020)	China	EVs	ABM, Utility: Likelihood ratio test	100 times	MATLAB	Enviornment awareness, Daily	Social network utility is significant postive on EV

						travelling distance	diffusion; The stronger of consumers' heterogeneity and the higher of customer indegreethe, the faster speed of EVS;
L. Sun and Lubkeman (2021)	/	EVs	Agent-based diffusion model,Logistic regression model	30 years	Monte Carlo simulation	Purchase price, Charging station	The decreased price of EV can decrease the stress to the feeder; Charging station in early station of distribution transformers can alleviate adverse impact.
C. Zhuge, Dong, Wei, and Shao (2021)	China	PHEV, BEV	SelfSim-EV model: demographic evolution model, transport facility development model, activity facility development model, Multinomial logit model	2016-2020	MATSim	Battery Cost, Battery Capacity, Battery Swap Station, Fast Charging Post	Technology innovations in battery decreased battery cost and increased battery capacity; Charging infrastructure in techonology innovation can promote EV uptake; Fast charging is no significant.
Buchmann, Wolf, and Fidaschek (2021)	Germany	PHEV,BEV	EMOSIM (Electric Mobility Simulation Model)	2020-2030	NetLogo	Vehcile-related factors, Social network, Household-specific and mobility-related, Infrastructure	Extension of federal incentives would not effective in long run; Direct monetary subsidies up to €6000, stronger funding of infrastructure and additional fuel taxes are more effective on promotion.

9.3. Agent-based model for the Italian and Chinese car market

9.3.1. Model description

The study is supposed to simulate the conversion of young people purchasing from ICEVs to EVs to investigate the possible demand features on the passenger car market up to the year 2030. We have used the software of AnyLogic to simulate the dynamic influence. AnyLogic is a multi-method simulation modeling tool combined with theories, allowing users to extend their simulation models with Java code. It supports agent-based models, discrete events, and system dynamics simulation (Borshchev, 2013). Modeling is one of the critical simulation ways in AnyLogic; it can connect actual market data with models and solve problems that are appeared in the real world.

it is characterized as a dynamic system model in which consumers (agents) make optimal decisions by considering a combination of factors. The agents' preferences remain constant during the simulation process, and they are monthly buyers based on their preference utility function. They have heterogeneous preferences and will consider their decisions based on the attributes of the products (net purchase price and driving range). The consumers' behaviors are changed based on their social network impacts, and the process is described as follows. Automakers for the EVs will adjust their selling price with technology improvements, and manufacturers will adjust their production costs in response to EV market demand. The sales price will change, then consumers will adjust their purchase decisions on EVs. However, consumers may make decision changes because of the market demand lag. Therefore, we have given assumptions in our ABM: agents are potential adopters but not car owners; information in the social network will keep constant in the whole diffusion process; the brands of cars would not influence consumers' choices; the external environment of consumers purchase is stable, and they will not delay their purchasing decision when they need to replace the car with a new one. To build the ABM model, we have followed the guidelines proposed in the study of Scorrano and Danielis (2021c). The simulation decision process is illustrated in Figure 6.

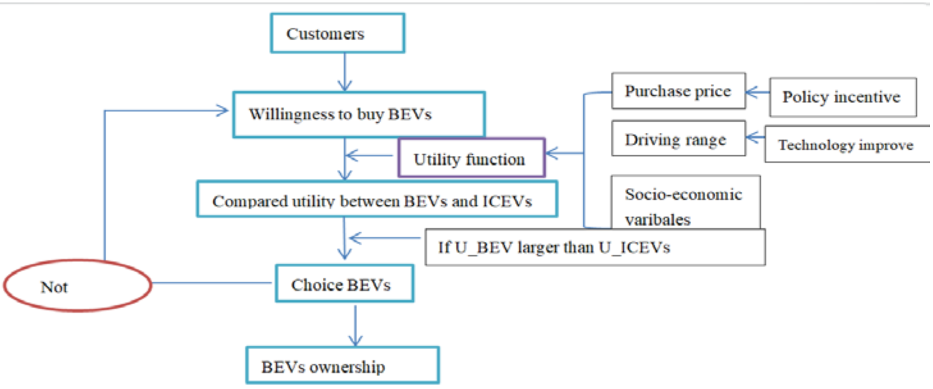


Figure 6 The vehicle purchase simulation decision chart

9.3.2. **Model Parameterization**

Agents

Customers (agents) are the essential building blocks in our ABM model. They have heterogeneity preference and bounded rationality in the model, reflecting their actions and reactions specified in different ways. In the case of a new purchase for customers, external factors and internal factors can both influence their choices. The external factors, originating from the environment or service providers, have similar effects on all customers. Scorrano and Danielis (2021c) have found that advertisement and social interaction can influence the number of car buyers. Proper modeling and assessment of the choice set are essential in initial ABMs concerning BEVs adoption. This is also found by Klein et al. (2020a), who have found consumers would make their new choice based on their current limited information obtained from advertisements, personal communication, and previous experiences. The internal factors, including customer preference structures, vehicle characteristics, and individual socioeconomic characteristics, have different performances on the choices. The internal dynamic customer behaviors can be captured using system dynamics, or discrete event approaches in ABM. The consumer may not choose BEVs only if BEVs are cost-effective when they face a choice to choose a new car. The rules for consumers to choose between BEVs and ICEVs depend on their preference structure, car characteristics, and socioeconomic characteristics (Scorrano & Danielis, 2021c). The attributes ion is included the net purchase price and fully charged driving range for one time. The utility function is expressed as the probability of individuals choosing cars; it is composed of the alternative specific constants (ASC), price and driving range attributes, socioeconomic characteristics, and error items. We have used an alternative specific constant (ASC) to capture the other variables not included in the function, which might influence consumers' decisions. The probability of consumers choosing a BEV is evaluated using the parameters in our MXL model with normal distribution.

All the agents in our model are exogenous and do not react to any model dynamics. Customers will make their choices when the BEVs are available, but the perception delay might increase the time of their decisions; when the BEVs are not available from producers, customers will delay their choices (Scorrano & Danielis, 2021c). All the consumers in our ABM model are considered potential adopters who are recognized as able to take but not necessarily purchase or use a BEV because they will check for availability from the sellers. If the BEV is not available, they will reevaluate their decisions and delay the choices for a period. We have given a strong assumption on agents' estimated preference structure that their preference will keep constant until 2030. The assumption is strict that this might cause an underestimation of the uptake of BEVs because consumers would likely change their choices when they have new driving experiences.

Vehicles

There are sevral propulsion system cars in our model, including Petrol, Diesel, LPG, CNG, BEV, HEV, PHEV. The characteristic of vehicles is performed with the net purchase price, driving range, and propulsion system types (Buchmann et al., 2021). With the estimated parameters in our MXL model, the parameters of the purchase price on BEVs were a highly significant and negative influence on the utility of BEVs. The values might change over time because of policy incentives and technology improvement, and all these changes are set as exogenous parameters. Taking into account the improved battery technology, we have considered driving range would be increased but limited; that is, when the driving range has been raised a specific value to 700 km, it would not significantly affect customer's preferences anymore (Buchmann et al., 2021).

Producers

The producers in our model were chosen based on the actual market distribution. We have mainly focused on the manufacturers who paid more attention to advertising their vehicles or vehicle attributes of price and range. They are considered to supply parts. Considering the cars with different propulsion systems, we have chosen the top five best-selling cars in the current market during our surveys.

9.3.3. Simulation environment and implication

Our ABM model has three hierarchical levels: individuals, networks, and population. The characteristics of the population are captured by individual state variables and connected with each other by social networks. Each level includes various variables; more details are listed in Table 31 .

Some global variables are also included in our ABM model. They are not directly related to the three hierarchical levels. One of the critical global variables is the purchase price of EVs. As the most crucial financial attribute in all reviewed studies, the purchase price has played significant negative signs in the utility of EVs. It assumes that the utility of EVs increased with the purchase price decreased over time. The assumption of decreased price is based on technology improvement and decreased battery costs. Specifically, technological advancement, economies of scale, and competition among brands are assumed to reduce the manufacturer's suggested retail prices between BEVs and ICEVs (Scorrano & Danielis, 2021c). The other crucial global variable is the driving range with a full tank or full battery charge for one time. It has been mentioned to have a significant positive effect on the utility of EVs (Beck et al., 2017; Cherchi, 2017; Danielis et al., 2020; Ghasri et al., 2019; Guerra & Daziano, 2020; Hahn et al., 2018; Huang & Qian, 2018; F. Liao et al., 2018; L. Rotaris et al., 2021). For BEVs, the driving range is limited in the current stage, and consumers would not purchase BEVs as additional vehicles if the driving range is shorter than 300km (Gu et al., 2019). However, as the battery technology improves, the driving range will be increased but are still limited. This implies that when the driving range rises to a specific value of 700 km, it would not be expected to influence customers' preference compared with fueled cars (Buchmann et al., 2021). In our sample, we assumed the purchase price of BEVs would decrease by 1% monthly until 2030. All simulation experiments are conducted in AnyLogic 8.8.0.

9.3.4. **Calibration and Validation**

For agent-based models in the economic field, researchers have proposed different types of the calibration method. H. Zhang and Vorobeychik (2019) considered calibration a quantitative process fitting a set of model parameters to data. Buchmann et al. (2021) have summarized three calibration approaches in ABM: the Werker–Brenner calibration, the indirect calibration, and the history-friendly calibration. However, we have just collected data in recent year, not enough data for the history-friendly calibration.

There are two standard methods used in model validation: validated by historical data and expert validation (H. Zhang & Vorobeychik, 2019). Considering the lack of history-friendly data in our collected database, we have decided to follow the method in the study of Scorrano and Danielis (2021c), compared our ABM results with the ones which we have obtained in the discrete choice model, assuming the actual and expected value of the demand attributes.

9.3.5. **Scenario description**

The scenario in our ABM is focused on the potential effects that adjusting the decreased purchase prices and increased driving range on the uptake of BEVs. For each individual, they are asked to make their decisions based on the characteristics with purchase price and driving range of cars. The purchase price of BEVs will be decreased by 1% each month, the driving range will be increased by 1% per month until 2030. The utility of BEVs is calculated for every car option regarding socio-economic characteristics, purchase price and driving range. Each individual will evaluate the utility of BEVs compared with the other cars and choose the highest utility of cars. That means, if the utility of BEVs is higher than the other cars, they will choose the BEVs, otherwise, they will continue to compare the other cars until they have chosen the highest utility among the left cars of propulsion systems. The process is listed in Figure 7.

We have examined three scenarios on the diffusion of BEVs in the two markets separately: price decreased scenario, technological progress scenario in the increased driving range, and price decreased and technological improvement simultaneously. Each scenario is simulated from January 2019 to December 2030, each consumer agent will purchase at least one vehicle during the simulation process.

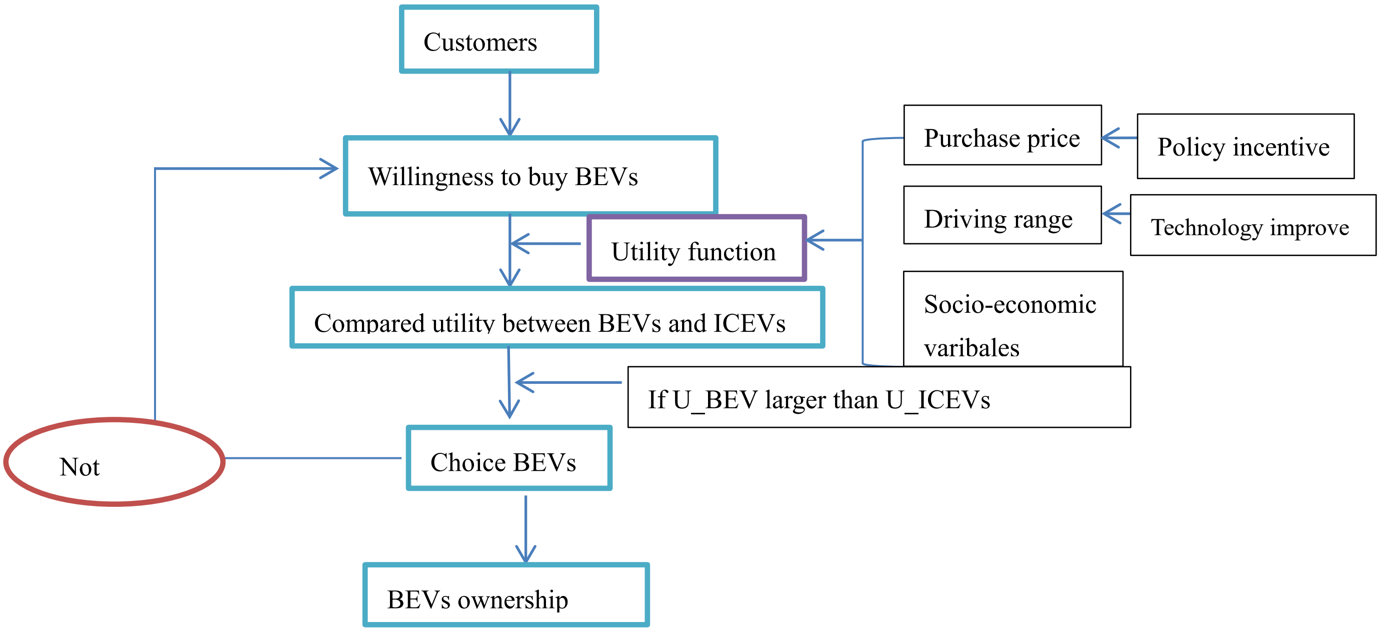


Figure 7 Simplified Schematic Representation of ABM

Table 31 Parameters listed in Anylogic

Entity	Variables	Description	Value
Vehicle agent	U_EV	Utility of EV	U_EV=ASC_EV +b_gender +b_charge +b_price*Price_EV+b_range_EV*Range_EV;
	U_Petrol/Diesel/LPG/CNG/HEV/PHEV	Utility of ICE	U_ICE=ASC_Petrol+b_price*Price_Petrol+b_range_ICE*Range_Petrol
	Price_EV_	Current purchase price of EV in real market	Price_EV_initial =18, the price unit is as the same as we used in R database)
	Price_Petrol/Diesel/LPG/CNG/HEV/PHEV	Purchase price of ICE	Price_Petrol/Diesel/LPG/CNG/HEV/PHEV(real market prices:16,30,13,16,11,42, the price unit is as the same as we used in R database)
	Range_EV	Driving range of EV	320
	Range_Petrol/Diesel/LPG/CNG/HEV/PHEV	Driving range of ICE	844,1154,675,400,754,1020 (real market price)
	b_price	The coefficient of purchase price	-0.147(got from MNL model)
	b_range_EV	The coefficient of driving range of EV	0 (not significant in Italy)
	b_range_ICE	The coefficient of driving range of ICE	0.004
	ASC_EV/Petrol/Diesel/LPG/CNG/HEV/PHEV	Alternative specific constants	2.351,0,0.327,0,-0.849,0.367,-0.893 (got from MNL Italy model)
Individual agent	b_gender	The coefficient of gender	self.Male_IT == Men_IT ? 1.303869:0
	b_charge	The coefficient of charging availability near work or home place	self.Charge_ava_IT == Charge_IT ? -0.497025:0
		The distribution defining probabilities for Male and Female	Option list, set as Male and Female
	Charge_Distribution	The distribution defining probabilities for charging availability or not	Option list, set as Charge and No Charge
Global	Choose_EV/Petrol/Diesel/LPG/CNG/HEV/PHEV	The function will return the value of chosen probability of cars	Prob=zidz(exp(U_EV),exp(U_EV)+exp(U_Petrol)+exp(U_Diesel)+exp(U_LPG)+exp(U_CNG)+exp(U_HEV)+exp(U_PHEV)); randomTrue(prob);
	EV/Petrol/Diesel/LPG/CNG/HEV/PHEV_Buyer	Potential buyer for EV/Petrol/Diesel/LPG/CNG/HEV/PHEV	\
	Share_EV/Petrol/Diesel/LPG/CNG/HEV/PHEV	Market share of EV/Petrol/Diesel/LPG/CNG/HEV/PHEV	EV_Buyer/max(1,EV_Buyer+Petrol_Buyer+Diesel_Buyer+LPG_Buyer+CNG_Buyer+HEV_Buyer+PHEV_Buyer)
	event_price	The event to describe the purchase price of EV decreased 1% each month	Price_EV=0.99*Price_EV;
	event_Utility_EV	The event to describe the utility of EVs will be increased with 1%decreased purchase price each month	U_EV=ASC_EV+b_gender+b_charge+b_price*Price_EV+b_range_EV*Range_EV;

9.4. **Simulation results**

The simulation parameters are used from the mixed logit model in Italy and China automobile markets in 2021. The model proceeds in monthly time steps. The results are listed in Table 32. The simulation model selected the actual best-selling model of Fiet 500e as the representative model in the Italian sample and the model of BYD Han EV in the Chinese sample. The simulation choice was performed in Figure 8.

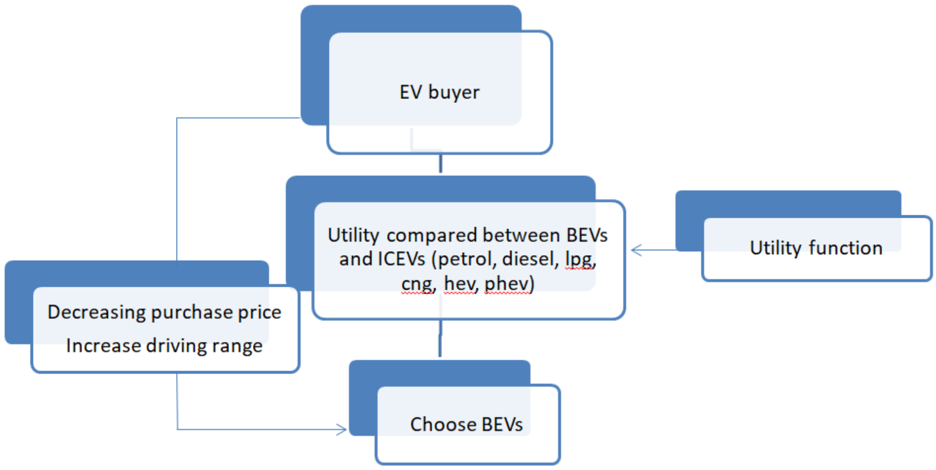


Figure 8 Simulation choice process for agent

Scenario 1 is focused on the price decrease. In January 2019, for the Italian market, the price of a BEV was €26,150, and the market share of BEVs in Italy was 3.03%. Although the Italian government implemented €6000 subsidy on BEVs in 2019, the share of car buyers to choose BEVs is still lower than fueled cars (Danielis et al., 2020; Scorrano et al., 2020). The simulation model predicts that BEV sales will start from January 2019, when the purchase price will decrease by 1% per month until 2030. Corresponding with the decreased purchase price, the simulated market share of BEVs in Italy is only 0.6%. Meanwhile, we have also simulated the Chinese market. The price of BEV in actual market in China is €25,000, and the market share was 7.95% in January 2019. When we carried out our simulation model in the Chinese market, the market share of BEVs in China increased to 5.8%. The simulate results in both two countries are much lower than that in actual market, this implies that the impact of price decreased on BEVs in our sample would be smaller.

Scenario 2 is related to the increased range of BEVs. The event in this scenario is that range increased by 1% per month until 2030. As expected, increased driving range causes a higher uptake of BEVs. The simulation market share in Italy and China has increased much higher than in the current market. Specifically, the share of BEVs in Italy, which is 79.6%, exceeds the share of petrol cars. This also confirmed the range anxiety that existed in the adoption of BEVs. However, the simulation market share of BEVs in Italy varied between 77.0% and 79.6 % in 2030, while the one in China varied between 24.6% and 32.8%, not very significantly decreased. This implies that, although the increased range would increase the uptake of BEVs, it would not significantly affect customers' preferences when a specific value has raised the driving range to 700 km (Buchmann et al., 2021).

Scenario 3 simulates the decreased price and increased range simultaneously. The simulated market shares of BEVs in both two markets increase higher than the actual market, specifically for the Chinese market (60.4%), it would lead a substantially increased than that with single simulation scenario.

Table 32 The simulation results of ABM in the car market

	Italy			China		
	Scenario 1	Scenario 2	Scenario 3	Scenario 1	Scenario 2	Scenario 3
BEV	0.6%	79.6%	65.4%	5.8%	32.8%	60.4%
Petrol	25.4%	5.2%	8.8%	50.7%	36.2%	21.3%
Diesel	10.7%	2.2%	3.7%	2.2%	1.5%	0.9%
LPG	11.4%	2.3%	4.0%	\	\	\
CNG	0.8%	0.2%	0.3%	\	\	\
HEV	50.8%	10.5%	17.7%	37.8%	27%	15.9%
PHEV	0.3%	0.1%	0.1%	3.5%	2.5%	1.5%

Note: Scenario 1-Decreased Price, Scenario 2-Increased Range, Scenario 3-Decreased Price and Increased Range

9.5. **Conclusion**

The study has developed an agent-based model to research the agents' choices between fueled cars and BEVs. Then we simulated the future market of BEVs by using the ABM approach. Our model included three scenarios: decrease price, increase driving range, decrease price and increase driving range simultaneously over the next ten years.

The main findings are the following. As the results of our discrete choice model have confirmed, purchase price and range were the two significant attributes of the utility of BEVs. Therefore, good performance on the price and range might cause high acceptance in the market of BEVs. Considering heterogeneous preference in both two markets, price reduction will not increase the market share of BEVs in both two samples in the 2030. The other policy implication on financial incentives could be considered, such as subsidies, as Scorrano and Danielis (2021c) found that even if subsidies were gradually reduced, it would not hamper the market share of BEVs up to 2030.

Moreover, previous studies have confirmed that the attribute of the range significantly influences the acceptance of BEVs (Adepetu & Keshav, 2017; Klein, Lüpke, & Günther, 2020b; Scorrano & Danielis, 2021c). Policy implication on the increased driving range of BEVs in both countries is likely an influential driving force for the uptake of BEVs in the following decades. Specifically, in the Italian market, it will increase to 79.6% by 2030, higher than the petrol cars when the heterogeneous preference existed in the Italian BEVs market. The simulation result is consistent with the finding of Hao, Lin, Wang, Ou, and Ouyang (2020), which confirmed the range anxiety in EVs market. Considering the socioeconomic variables, the possible buyers would likely be the ones who have a garage for charging.

When the implication of decreased price and increased range were jointly applied to our model, the market share of BEVs increased significantly. This is also confirmed in the study of Buchmann et al. (2021), which has found that currently implemented policies with additional measures such as carbon tax on fuel, more charging points, and higher direct subsidies might facilitate the goal of high uptake on BEVs. Although some technological barriers still exist in the current stage, technological progress and financial incentives will promote BEV uptake in the next year.

However, our study had some limitations when we carried out the simulation. Our study focuses on the young group, there might be high uncertainty due to their limited personal driving experience and less information on BEVs; this could cause deviation preference which would influence the heterogeneity preferences of respondents. Further improvements would focus on enlarging the groups to capture heterogeneity. Moreover, the current attributes in our model do not include other potential vehicle attributes, such as cost, charging time, and charging density, which would cause effects the uptake of BEVs, we will increase more scenario analysis on incentives in the future work.

Moreover, all values we have simulated are set equal in the scenarios; our target market group is the young group and does not include the whole new car market; the preferences remain constant during the simulation process. This strong and simplifying assumption might cause an underestimation in market trends. The scenario of decreased price and increased range in our ABM do not consider any cross-effects; this might cause some bias on the impacts of social networks. The assumption of the estimated preference of agents is constant until 2030, and we would consider the dynamic preference on timing aspects in future works.

10. Conclusions, Limitations and Suggestions for Future Research

10.1. **Conclusions and policy implications**

The main research questions of this study is included: 1. what are the main attributes influencing the consumers' car choice, 2. what are the main socio-economic determinants in choosing a car, 3. what are the main latent variable that influence the consumers' car choice, 4. how will the car market develop in the next years. This study aims to investigate the similarities and differences among prospective EV buyers in Italy and China and to explore the effects of attributes (purchase price and driving range) and attitudes on the uptake of BEVs. The obvious difference is the market share of BEVs. In Italy, the share is increased but still in the early stages, while In China, the share of BEVs is significantly increased. We uses the discrete choice model to explore the stated preference of respondents, then uses an agent-based model to simulate the diffusion of BEVs. We also conducted a model application on the key price and range attributes to evaluate the potential market share changes for each alternative in two markets. The data collection was performed by web-based version which was conducted from March to November 2021. The dataset included 436 respondents in Italy and 358 respondents in China. The summarized conclusions are listed in Table 33.

Our econometric models confirmed that the financial attribute (i.e., the purchase price) and the non-financial attribute (i.e., the driving range) strongly affected EV demand in both countries, as expected. Heterogeneity preference exists among respondents. We have found that a more extended driving range would increase preference for EVs. With the analysis of the stated choices performed with the MXL model, the main difference of our findings in comparison with previous studies is that we have confirmed the role of driving range in the Italy market and found that Italians are more range sensitive. This also indicates that the driving range issue still needs to be solved on the uptake of BEVs in the Italian market.

Some of the socioeconomic variables played significant roles on the utility of BEVs in our samples. In our MNL model, garage charging availability for BEVs plays a significantly positive role in Italy and China. Men are more likely to choose BEVs than women for the Italian sample. While people who have a high household income are more likely to choose BEVs in China. This indicate that BEVs adopters tend to concentrate on the ownership of charging garage, high income levels.

The analysis of the stated choices performed with the MXL model confirmed that garage charging availability plays a significantly positive role in Italy. This finding was improved in our Italian sample, as previous studies cannot confirm the significant role of garage ownership on the uptake of the Italian market. If Italy wants to increase the uptake level of BEVs, it should pay more attention to the charging infrastructure in favor of BEVs. Although China has a larger geographical size, the garage charging availability was not significant. Income level and gender does not play significant roles in both countries when we have considered the heterogeneity preference.

Furthermore, the data responds to attitudinal statements regarding the environment, skepticism, economic issue, and performance. We have used factor analysis to extract latent variables, labled “Not skeptical about EVs”, “Late adopter”, “Not an environmental friendly way”, and “EVs are fast, safe and fun to drive”. We have found the hybrid model specification is better at explaining the choice process. All the latent variables are significant in Italy, women who with environmental awarenessare are more likely to choose EVs, and respondents with a high income level and people who own more cars are more likely to choose EVs. However, our finding does not confirm any significant effect on the environmental friendly awareness for Chinese.

For the model application, compared with no incentives, all the policy incentives are effective in promoting the uptake of BEVs; however, the policy on price reduction in Italy is still weak. Multiple price and range policies are more effective than a single policy in EVs markets in both countries. These provide some suggestions to increase BEV uptakes, such as purchase price subsidies and technical improvement on driving range extension. Although the initial market stage has yet to be apparent, positive external sources, including multiple price and range policies, could strengthen the uptake of BEVs. Government should consider consistent support for the expansion of public charging infrastructure.

The diffusion results can simulate the process of a low market share at the initial stage and a rapid increase in the market share of BEVs in the following decades. Considering the effect of diffusion, the results of ABM indicated that policy implication on the increased driving range of BEVs in both countries is likely an influential driving force for the uptake of BEVs in the following decades. The combination of two policies is more effective than a single policy implication to promote the development of BEVs. However, the impact of direct price decreases on BEVs is slight; a single price reduction policy cannot effectively stimulate the promotion of BEVs at the current stage. The government can consider shifting subsidies to the market, looking for the most effective combination strategy.

Table 33 Summarized conclusions in Italian and Chinese market

Research questions	Conclusions
1. What are the main attributes influencing the consumers’ car choice?	• Purchase Price and Driving range play a significant role in both two countries • Price and range heterogeneity preference is existed, Italians are range sensitive in MXL model
2. What are the main socio-economic determinants in choosing a car?	• In MNL model, garage charging availability plays a significant positive role. In Italy, men have a stronger preference for BEVs than women, People who live in large cities assign a higher utility to BEV; In China, gender, income and city size plays no significant role • In MXL model, only Italians are more sensitive on the socioeconomic variables of garage charging aviability

3.What are the main latent variable that influence the consumers' car choice?	• All latent variables related with driving range(positive), environment friendly(negative), charging points(positive) and policy incentives (positive) played significant roles in Italy • There is no significant finding for environment friendly attitude in China
4. How will the car market develop in the next years?	• Multiple price and range policies are more effective than a single policy in EVs markets in both countries in model application • In ABM, increased driving range of BEVs or multiple policy on price and range would enhance BEV diffusion significantly, single price reduction policy is not effective in both two countries

10.2. **Limitaions and future work**

Our study had some limitations. Some vehicles were not available in the car markets when the respondents bought their cars, and the choice sets were inconsistent when the respondents made their actual car choices. Specifically, some families had already bought their own cars before EVs appeared in the market, so this might have made their choice sets inconsistent with their actual choices and might have caused choice bias in our statistical estimation. Although our selected attributes had a significant impact on the consumers' preferences for BEVs, this does not mean that the other attributes, including psychological attributes, are not relevant to the uptake of BEVs. We will increase more attributes analysis on incentives to test the impacts that were not included in the current work.

Moreover, our study focuses on the young group; there might be high uncertainty due to their limited personal driving experience and less information on BEVs; this could cause deviation preference which would influence the heterogeneity preferences of respondents. Further improvements would focus on enlarging the groups to capture heterogeneity. In addition, we collected attitudes information through web-based interviews. Although it can reduce the collection cost, due to the respondents' limited knowledge, that could affect their choices when they had to select the responses in the survey questionnaire. We will try to do some preparatory work in our future research to overcome the cognitive limitations, such as collecting data in person and doing some propagate activity before launching the survey.

Furthermore, the preferences assumption of our agent-based model remains constant during the simulation process; this is strict and simplifying, which might cause some bias on the impacts of social networks, so we will consider a dynamic preference on timing aspects in future works.

Reference

Abotalebi, E., Scott, D. M., & Ferguson, M. R. (2019). Why is electric vehicle uptake low in Atlantic Canada? A comparison to leading adoption provinces. *Journal of Transport Geography, 74*, 289-298.

ACEA. (2022a). New passenger car registrations in the EU by alternative fuel type in full-year 2021. from European Automobile Manufacturers' Association (ACEA) https://www.acea.auto/fuel-pc/fuel-types-of-new-cars-battery-electric-9-1-hybrid-19-6-and-petrol-40-0-market-share-full-year-2021/

ACEA. (2022b). Vehicles in use Europe 2022. from European Automobile Manufacturers' Association (ACEA) https://www.acea.auto/publication/report-vehicles-in-use-europe-2022/

ACEA. (2023). New passenger car registrations in the EU by alternative fuel type. from European Automobile Manufacturers' Association (ACEA)

Adepetu, A., & Keshav, S. (2017). The relative importance of price and driving range on electric vehicle adoption: Los Angeles case study. *Transportation, 44*(2), 353-373.

Ahkamiraad, A., & Wang, Y. (2018). An agent-based model for zip-code level diffusion of electric vehicles and electricity consumption in New York City. *Energies, 11*(3), 640.

Ajzen, I. (1991). The theory of planned behavior. *Organizational behavior and human decision processes, 50*(2), 179-211.

Ashkrof, P., Homem de Almeida Correia, G., & van Arem, B. (2020). Analysis of the effect of charging needs on battery electric vehicle drivers' route choice behaviour: A case study in the Netherlands. *Transportation Research Part D: Transport and Environment, 78*, 102206.

Bailey, J., & Axsen, J. (2015). Anticipating PEV buyers' acceptance of utility controlled charging. *Transportation Research Part A: Policy and Practice, 82*, 29-46.

Barth, M., Jugert, P., & Fritsche, I. (2016). Still underdetected–Social norms and collective efficacy predict the acceptance of electric vehicles in Germany. *Transportation research part F: traffic psychology and behaviour, 37*, 64-77.

Beck, M. J., Fifer, S., & Rose, J. M. (2016). Can you ever be certain? Reducing hypothetical bias in stated choice experiments via respondent reported choice certainty. *Transportation Research Part B: Methodological, 89*, 149-167.

Beck, M. J., Rose, J. M., & Greaves, S. P. (2017). I can't believe your attitude: a joint estimation of best worst attitudes and electric vehicle choice. *Transportation, 44*(4), 753-772.

Ben-Akiva M., McFadden D., & K., T. (2002). Hybrid choice models: Progress and challenges. *Marketing Letters, 13*(3), 163-175.

Berkeley, N., Jarvis, D., & Jones, A. (2018). Analysing the take up of battery electric vehicles: An investigation of barriers amongst drivers in the UK. *Transportation Research Part D: Transport and Environment, 63*, 466-481.

Bollen, K. A. (1989). *Structural equations with latent variables* (Vol. 210): John Wiley & Sons.

Borshchev, A. (2013). *The big book of simulation modeling: multimethod modeling with AnyLogic 6*: AnyLogic North America.

Brown, M. (2013). Catching the PHEVer: simulating electric vehicle diffusion with an agent-based mixed logit model of vehicle choice. *Journal of Artificial Societies and Social Simulation, 16*(2), 5.

Buchmann, T., Wolf, P., & Fidaschek, S. (2021). Stimulating E-Mobility Diffusion in Germany (EMOSIM): An Agent-Based Simulation Approach. *Energies, 14*(3), 656.

CAAM. (2022). Production and sales of the automobile industry in 2022. from China Association of Automobile Manufactures (CAAM) http://www.caam.org.cn/index.html

Campisi, T., Ignaccolo, M., Tesoriere, G., Inturri, G., & Torrisi, V. (2020). The evaluation of car-sharing to raise acceptance of electric vehicles: evidences from an italian survey among university students: SAE Technical Paper.

Carrese S., Giacchetti T., & Nigro M. (2017). An innovative car sharing electric vehicle system: An Italian experience. *Urban Transport XXIII, 23*(176), 245.

Cartenì, A., Cascetta, E., & de Luca, S. (2016). A random utility model for park & carsharing services and the pure preference for electric vehicles. *Transport Policy, 48*, 49-59.

Cherchi, E. (2017). A stated choice experiment to measure the effect of informational and normative conformity in the preference for electric vehicles. *Transportation Research Part A: Policy and Practice, 100*, 88-104.

Child, D. (2006). *The essentials of factor analysis*: A&C Black.

Cirillo, C., Liu, Y., & Maness, M. (2017). A time-dependent stated preference approach to measuring vehicle type preferences and market elasticity of conventional and green vehicles. *Transportation Research Part A: Policy and Practice, 100*, 294-310.

CMPS. (2022). National motor vehicle ownership in 2021. from Ministry of Public Security of the People's Republic of China (CMPS) https://www.mps.gov.cn/n2254314/n6409334/c8322353/content.html

Coffman, M., Bernstein, P., & Wee, S. (2017). Electric vehicles revisited: a review of factors that affect adoption. *Transport Reviews, 37*(1), 79-93.

Comrey, A. L., & Lee, H. B. (2013). *A first course in factor analysis*: Psychology press.

Costello, A. B., & Osborne, J. (2005). Best practices in exploratory factor analysis: Four recommendations for getting the most from your analysis. *Practical assessment, research, and evaluation, 10*(1), 7.

CPCA. (2022). Statistic data in 2021. from China Passenger Cars Association (CPCA) http://data.cpcaauto.com/

CPCA. (2023). The analysis of the new energy market in December 2022. from China Passenger Cars Association (CPCA) http://data.cpcaauto.com/

Crutchfield, R. S. (1955). Conformity and character. *American psychologist, 10*(5), 191.

Danielis, R., Giansoldati, M., & Rotaris, L. (2018). A probabilistic total cost of ownership model to evaluate the current and future prospects of electric cars uptake in Italy. *Energy Policy, 119*, 268-281.

Danielis, R., Rotaris, L., Giansoldati, M., & Scorrano, M. (2020). Drivers' preferences for electric cars in Italy. Evidence from a country with limited but growing electric car uptake. *Transportation Research Part A: Policy and Practice, 137*, 79-94.

de Luca, S., Di Pace, R., & Bruno, F. (2020). Accounting for attitudes and perceptions influencing users' willingness to purchase Electric Vehicles through a Hybrid Choice Modeling approach based on Analytic Hierarchy Process. *Transportation research procedia, 45*, 467-474.

de Luca, S., Di Pace, R., & Marano, V. (2015). Modelling the adoption intention and installation choice of an automotive after-market mild-solar-hybridization kit. *Transportation Research Part C: Emerging Technologies, 56*, 426-445.

dos Santos, F. L. M., Tecchio, P., Ardente, F., & Pekár, F. (2021). User automotive powertrain-type choice model and analysis using neural networks. *Sustainability, 13*(2), 1-15.

Ensslen, A., Will, C., & Jochem, P. (2019). Simulating electric vehicle diffusion and charging activities in France and Germany. *World Electric Vehicle Journal, 10*(4), 73.

EVCIPA. (2023). The report of electric vehicle charging infrastructure in 2022. from China Electric Vehicle Charging Infrastructure Promotion Alliance(EVCIPA) http://www.evcipa.org.cn

Fang, Y., Wei, W., Mei, S., Chen, L., Zhang, X., & Huang, S. (2020). Promoting electric vehicle charging infrastructure considering policy incentives and user preferences: An evolutionary game model in a small-world network. *Journal of Cleaner Production, 258*, 120753.

Ferguson, M., Mohamed, M., Higgins, C. D., Abotalebi, E., & Kanaroglou, P. (2018). How open are Canadian households to electric vehicles? A national latent class choice analysis with willingness-to-pay and metropolitan characterization. *Transportation Research Part D: Transport and Environment, 58*, 208-224.

Figenbaum, E. (2020). Battery electric vehicle fast charging–evidence from the Norwegian market. *World Electric Vehicle Journal, 11*(2), 38.

Ge, Y., MacKenzie, D., & Keith, D. R. (2018). Gas anxiety and the charging choices of plug-in hybrid electric vehicle drivers. *Transportation Research Part D: Transport and Environment, 64*, 111-121.

Ghasri, M., Ardeshiri, A., & Rashidi, T. (2019). Perception towards electric vehicles and the impact on consumers' preference. *Transportation Research Part D: Transport and Environment, 77*, 271-291.

Giansoldati, M., Monte, A., & Scorrano, M. (2020). Barriers to the adoption of electric cars: Evidence from an Italian survey. *Energy Policy, 146*, 111812.

Giansoldati, M., Rotaris, L., Scorrano, M., & Danielis, R. (2020). Does electric car knowledge influence car choice? Evidence from a hybrid choice model. *Research in Transportation Economics, 80*, 100826.

Gnann, T., Funke, S., Jakobsson, N., Plötz, P., Sprei, F., & Bennehag, A. (2018). Fast charging infrastructure for electric vehicles: Today’s situation and future needs. *Transportation Research Part D: Transport and Environment, 62*, 314-329.

Gnann, T., Plötz, P., & Wietschel, M. (2019). Can public slow charging accelerate plug-in electric vehicle sales? A simulation of charging infrastructure usage and its impact on plug-in electric vehicle sales for Germany. *International Journal of Sustainable Transportation, 13*(7), 528-542.

Gomez Vilchez, J. J., Smyth, A., Kelleher, L., Lu, H., Rohr, C.,, Harrison, G., & Thiel, C. (2019). Electric car purchase price as a factor determining consumers' choice and their views on incentives in Europe. *Sustainability, 11*(22), 6357.

Gong, S., Ardeshiri, A., & Rashidi, T. H. (2020). Impact of government incentives on the market penetration of electric vehicles in Australia. *Transportation Research Part D: Transport and Environment, 83*, 102353.

Greene, D., Hossain, A., Hofmann, J., Helfand, G., & Beach, R. (2018). Consumer willingness to pay for vehicle attributes: What do we Know? *Transportation Research Part A: Policy and Practice, 118*, 258-279.

Greene, W. H., & Hensher, D. A. (2003). A latent class model for discrete choice analysis: contrasts with mixed logit. *Transportation Research Part B: Methodological, 37*(8), 681-698.

Gu, G., & Feng, T. (2020). Heterogeneous choice of home renewable energy equipment conditioning on the choice of electric vehicles. *Renewable Energy, 154*, 394-403.

Gu, G., Yang, D., Feng, T., & Timmermans, H. (2019). Household vehicle holding decisions in response to life cycle events. *Transportation research procedia, 37*, 171-178.

Guerra, E. (2019). Electric vehicles, air pollution, and the motorcycle city: A stated preference survey of consumers’ willingness to adopt electric motorcycles in Solo, Indonesia. *Transportation Research Part D: Transport and Environment, 68*, 52-64.

Guerra, E., & Daziano, R. A. (2020). Electric vehicles and residential parking in an urban environment: Results from a stated preference experiment. *Transportation Research Part D: Transport and Environment, 79*, 102222.

Hackbarth, A., & Madlener, R. (2013). Consumer preferences for alternative fuel vehicles: A discrete choice analysis. *Transportation Research Part D: Transport and Environment, 25*, 5-17.

Hackbarth, A., & Madlener, R. (2016). Willingness-to-pay for alternative fuel vehicle characteristics: A stated choice study for Germany. *Transportation Research Part A: Policy and Practice, 85*, 89-111.

Hahn, J. S., Lee, J. H., & Choi, K. (2018). Heterogeneous preferences of green vehicles by vehicle size: Analysis of Seoul case. *International Journal of Sustainable Transportation, 12*(9), 675-685.

Hair, J. F. (2009). *Multivariate data analysis*.

Hao, X., Lin, Z., Wang, H., Ou, S., & Ouyang, M. (2020). Range cost-effectiveness of plug-in electric vehicle for heterogeneous consumers: An expanded total ownership cost approach. *Applied Energy, 275*, 115394.

Haustein, S., Jensen, A. F., & Cherchi, E. (2021). Battery electric vehicle adoption in Denmark and Sweden: Recent changes, related factors and policy implications. *Energy Policy, 149*, 112096.

Helveston, J. P., Liu, Y., Feit, E. M., Fuchs, E., Klampfl, E., & Michalek, J. J. (2015). Will subsidies drive electric vehicle adoption? Measuring consumer preferences in the US and China. *Transportation Research Part A: Policy and Practice, 73*, 96-112.

Henson, R. K., & Roberts, J. K. (2006). Use of exploratory factor analysis in published research: Common errors and some comment on improved practice. *Educational and Psychological measurement, 66*(3), 393-416.

Hess, S., & Train, K. (2017). Correlation and scale in mixed logit models. *Journal of choice modelling, 23*, 1-8.

Hesselink, L. X., & Chappin, E. J. (2019). Adoption of energy efficient technologies by households–Barriers, policies and agent-based modelling studies. *Renewable and Sustainable Energy Reviews, 99*, 29-41.

Higgins, C. D., Mohamed, M., & Ferguson, M. R. (2017). Size matters: How vehicle body type affects consumer preferences for electric vehicles. *Transportation Research Part A: Policy and Practice, 100*, 182-201.

Hu, L. T., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural equation modeling: a multidisciplinary journal, 6*(1), 1-55.

Huang, X., & Ge, J. (2019). Electric vehicle development in Beijing: An analysis of consumer purchase intention. *Journal of Cleaner Production, 216*, 361-372.

Huang, Y., & Qian, L. (2018). Consumer preferences for electric vehicles in lower tier cities of China: Evidences from south Jiangsu region. *Transportation Research Part D: Transport and Environment, 63*, 482-497.

Huijts, N. M., Molin, E. J., & Steg, L. (2012). Psychological factors influencing sustainable energy technology acceptance: A review-based comprehensive framework. *Renewable and Sustainable Energy Reviews, 16*(1), 525-531.

IEA. (2022). Global Energy Review: CO2 Emissions in 2021. from International Energy Agency (IEA) https://www.iea.org/data-and-statistics

IEA. (2023). Global EV Outlook 2022. from International Energy Agency (IEA) https://www.iea.org/reports/global-ev-outlook-2022/trends-in-charging-infrastructure

ISTAT. (2020). Annual report., from Italian National Institute of Statistics (ISTAT) https://www.istat.it/it/

Jackson, D. L., Gillaspy Jr, J. A., & Purc-Stephenson, R. (2009). Reporting practices in confirmatory factor analysis: an overview and some recommendations. *Psychological methods, 14*(1), 6.

Jensen, A. F., Cherchi, E., & Mabit, S. L. (2013). On the stability of preferences and attitudes before and after experiencing an electric vehicle. *Transportation Research Part D: Transport and Environment, 25*, 24-32.

Jensen, A. F., Cherchi, E., Mabit, S. L., & De Dios Ortúzar, J. (2017). Predicting the potential market for electric vehicles. *Transportation Science, 51*(2), 427-440.

Jeon, C., Yoo, J., & Choi, M. K. (2012). *The effect of social influence on consumers' hybrid electric vehicles adoption in Korea and China*. Paper presented at the In 2012 14th International Conference on Advanced Communication Technology (ICACT).

Jin, F., An, K., & Yao, E. (2020). Mode choice analysis in urban transport with shared battery electric vehicles: A stated-preference case study in Beijing, China. *Transportation Research Part A: Policy and Practice, 133*, 95-108.

Jochem, P., Gómez Vilchez, J. J., Ensslen, A., Schäuble, J., & Fichtner, W. (2018). Methods for forecasting the market penetration of electric drivetrains in the passenger car market. *Transport Reviews, 38*(3), 322-348.

Kahn, J. H. (2006). Factor analysis in counseling psychology research, training, and practice: Principles, advances, and applications. *The counseling psychologist, 34*(5), 684-718.

Kang, L. P., Earlay, R., & An, F. (2010). Policy Recommendations for Supporting the Development of Low Carbon Automotive Fuels in China *Energy Foundation* (Vol. 2020).

Kangur, A., Jager, W., Verbrugge, R., & Bockarjova, M. (2017). An agent-based model for diffusion of electric vehicles. *Journal of Environmental Psychology, 52*, 166-182.

Kiesling, E., Günther, M., Stummer, C., & Wakolbinger, L. M. (2012). Agent-based simulation of innovation diffusion: a review. *Central European Journal of Operations Research, 20*(2), 183-230.

Kim, J. H., Lee, G., Park, J. Y., Hong, J., & Park, J. (2019). Consumer intentions to purchase battery electric vehicles in Korea. *Energy Policy, 132*, 736-743.

Kleijnen, J. P. J. S. D. R. (1995). Sensitivity analysis and optimization of system dynamics models: regression analysis and statistical design of experiments. *11*(4), 275-288.

Klein, M., Lüpke, L., & Günther, M. (2020a). Home charging and electric vehicle diffusion: Agent-based simulation using choice-based conjoint data. *Transportation Research Part D: Transport and Environment, 88*. doi: 10.1016/j.trd.2020.102475

Klein, M., Lüpke, L., & Günther, M. (2020b). Home charging and electric vehicle diffusion: agent-based simulation using choice-based conjoint data. *Transportation Research Part D: Transport and Environment, 88*, 102475.

Kormos, C., Axsen, J., Long, Z., & Goldberg, S. (2019). Latent demand for zero-emissions vehicles in Canada (Part 2): Insights from a stated choice experiment. *Transportation Research Part D: Transport and Environment, 67*, 685-702.

Kroes, E. P., & Sheldon, R. J. (1988). Stated preference methods: an introduction. *Journal of transport economics and policy*, 11-25.

Le Pira, M., Marcucci, E., Gatta, V., Inturri, G., Ignaccolo, M., & Pluchino, A. (2017). Integrating discrete choice models and agent-based models for ex-ante evaluation of stakeholder policy acceptability in urban freight transport. *Research in Transportation Economics, 64*, 13-25.

Li, J., Jiao, J., & Tang, Y. (2020). Analysis of the impact of policies intervention on electric vehicles adoption considering information transmission—based on consumer network model. *Energy Policy, 144*, 111560.

Li, L., Wang, Z., & Wang, Q. (2020). Do policy mix characteristics matter for electric vehicle adoption? A survey-based exploration. *Transportation Research Part D: Transport and Environment, 87*, 102488.

Li, L., Wang, Z., & Xie, X. (2022). From government to market? A discrete choice analysis of policy instruments for electric vehicle adoption. *Transportation Research Part A: Policy Practice, 160*, 143-159.

Liao, F., Molin, E., Timmermans, H., & van Wee, B. (2018). The impact of business models on electric vehicle adoption: A latent transition analysis approach. *Transportation Research Part A: Policy and Practice, 116*, 531-546.

Liao, F., Molin, E., Timmermans, H., & van Wee, B. (2019). Consumer preferences for business models in electric vehicle adoption. *Transport Policy, 73*, 12-24. doi: 10.1016/j.tranpol.2018.10.006

Liao, F., Molin, E., Timmermans, H., & van Wee, B. (2020). Carsharing: the impact of system characteristics on its potential to replace private car trips and reduce car ownership. *Transportation, 47*(2), 935-970.

Liao, F., Molin, E., & van Wee, B. (2017). Consumer preferences for electric vehicles: a literature review. *Transport Reviews, 37*(3), 252-275.

Ling, Z., Cherry, C. R., & Wen, Y. (2021). Determining the Factors That Influence Electric Vehicle Adoption: A Stated Preference Survey Study in Beijing, China. *Sustainability, 13*(21), 11719.

Liu, Y., & Cirillo, C. (2018). Modeling green vehicle adoption: An integrated approach for policy evaluation. *International Journal of Sustainable Transportation, 12*(7), 473-483.

Louviere, J. J., Hensher, D. A., & Swait, J. D. (2000). *Stated choice methods: analysis and applications*: Cambridge university press.

Lu, T., Yao, E., Jin, F., & Pan, L. (2020). Alternative incentive policies against purchase subsidy decrease for Battery Electric Vehicle (BEV) adoption. *Energies, 13*(7).

Ma, S. C., Fan, Y., Guo, J. F., Xu, J. H., & Zhu, J. (2019). Analysing online behaviour to determine Chinese consumers' preferences for electric vehicles. *Journal of Cleaner Production, 229*, 244-255.

Ma, S. C., Xu, J. H., & Fan, Y. (2019). Willingness to pay and preferences for alternative incentives to EV purchase subsidies: An empirical study in China. *Energy Economics, 81*, 197-215.

Macal, C. M. (2016). Everything you need to know about agent-based modelling and simulation. *Journal of Simulation, 10*, 144-156.

MacCallum, R. C., Widaman, K. F., Zhang, S., & Hong, S. (1999). Sample size in factor analysis. *Psychological methods, 4*(1), 84.

McFadden, D., & Train, K. (2000). Mixed MNL models for discrete response. *Journal of applied Econometrics, 15*(5), 447-470.

Miceli, R., & Viola, F. (2017). Designing a sustainable university recharge area for electric vehicles: Technical and economic analysis. *Energies, 10*(10), 1604.

Miele, A., Axsen, J., Wolinetz, M., Maine, E., & Long, Z. (2020). The role of charging and refuelling infrastructure in supporting zero-emission vehicle sales. *Transportation Research Part D: Transport and Environment, 81*.

MOTUS-E. (2023). Market analysis. https://www.motus-e.org/

Mundaca, L., Neij, L., Worrell, E., & McNeil, M. (2010). Evaluating energy efficiency policies with energy-economy models. *Annual review of environment and resources, 35*, 305-344.

NBSC. (2020). *2020 China statistical yearbook*. Beijing: National Bureau of Statistics of China (NBSC) Retrieved from http://www.stats.gov.cn/english/.

Nie, Y., Wang, E., Guo, Q., & Shen, J. (2018). Examining Shanghai consumer preferences for electric vehicles and their attributes. *Sustainability, 10*(6), 2036.

Ning, W., Guo, J., Liu, X., & Pan, H. (2020). Incorporating individual preference and network influence on choice behavior of electric vehicle sharing using agent-based model. *International Journal of Sustainable Transportation, 14*(12), 917-931.

Noel, L., de Rubens, G. Z., Kester, J., & Sovacool, B. K. (2020). Understanding the socio-technical nexus of Nordic electric vehicle (EV) barriers: A qualitative discussion of range, price, charging and knowledge. *Energy Policy, 138*, 111292.

Noori, M., & Tatari, O. (2016). Development of an agent-based model for regional market penetration projections of electric vehicles in the United States. *Energy, 96*, 215-230.

Nykvist, B., Sprei, F., & Nilsson, M. (2019). Assessing the progress toward lower priced long range battery electric vehicles. *Energy Policy, 124*, 144-155.

Oliveira, G. D., Roth, R., & Dias, L. C. (2019). Diffusion of alternative fuel vehicles considering dynamic preferences. *Technological Forecasting and Social Change, 147*, 83-99.

Orlov, A., & Kallbekken, S. (2019). The impact of consumer attitudes towards energy efficiency on car choice: Survey results from Norway. *Journal of Cleaner Production, 214*, 816-822.

Palmer, J., Sorda, G., & Madlener, R. (2015). Modeling the diffusion of residential photovoltaic systems in Italy: An agent-based simulation. *Technological Forecasting and Social Change, 99*, 106-131.

Pan, L., Yao, E., & MacKenzie, D. (2019). Modeling EV charging choice considering risk attitudes and attribute non-attendance. *Transportation Research Part C: Emerging Technologies, 102*, 60-72.

Pearson, K. (1901). LIII. On lines and planes of closest fit to systems of points in space. *The London, Edinburgh, and Dublin philosophical magazine and journal of science, 2*(11), 559-572.

Pett, M. A., Lackey, N. R., & Sullivan, J. J. (2003). *Making sense of factor analysis: The use of factor analysis for instrument development in health care research*: Sage.

Qian, L., Grisolía, J. M., & Soopramanien, D. (2019). The impact of service and government-policy attributes on consumer preferences for electric vehicles in China. *Transportation Research Part A: Policy and Practice, 122*, 70-84. doi: 10.1016/j.tra.2019.02.008

Qian, L., & Soopramanien, D. (2011). Heterogeneous consumer preferences for alternative fuel cars in China. *Transportation Research Part D: Transport and Environment, 16*(8), 607-613.

Querini, F., & Benetto, E. (2014). Agent-based modelling for assessing hybrid and electric cars deployment policies in Luxembourg and Lorraine. *Transportation Research Part A: Policy and Practice, 70*, 149-161.

Reio Jr, T. G., & Shuck, B. (2015). Exploratory factor analysis: implications for theory, research, and practice. *Advances in Developing Human Resources, 17*(1), 12-25.

Rose, J. M., & Bliemer, M. C. (2009). Constructing efficient stated choice experimental designs. *Transport Reviews, 29*(5), 587-617.

Rotaris, L., & Danielis, R. (2019). The willingness to pay for a carbon tax in Italy. *Transportation Research Part D: Transport and Environment, 67*, 659-673.

Rotaris, L., Giansoldati, M., & Scorrano, M. (2020). The slow uptake of electric cars in Italy and Slovenia. Evidence from a stated-preference survey and the role of knowledge and environmental awareness. *Transportation Research Part A: Policy and Practice, 144*, 1-18.

Rudolph, C. (2016). How may incentives for electric cars affect purchase decisions? *Transport Policy, 52*, 113-120.

Rusich, A., & Danielis, R. (2015). Total cost of ownership, social lifecycle cost and energy consumption of various automotive technologies in Italy. *Research in Transportation Economics, 50*, 3-16.

Scorrano, M., & Danielis, R. (2021a). Active mobility in an Italian city: Mode choice determinants and attitudes before and during the Covid-19 emergency. *Research in Transportation Economics, 86*, 101031.

Scorrano, M., & Danielis, R. (2021b). The characteristics of the demand for electric scooters in Italy: An exploratory study. *Research in Transportation Business Management, 39*, 100589.

Scorrano, M., & Danielis, R. (2021c). Simulating electric vehicle uptake in Italy in the small-to-medium car segment: A system dynamics/agent-based model parametrized with discrete choice data. *Research in Transportation Business Management, 43*, 100736.

Scorrano, M., Danielis, R., & Giansoldati, M. (2020). Dissecting the total cost of ownership of fully electric cars in Italy: The impact of annual distance travelled, home charging and urban driving. *Research in Transportation Economics, 80*, 100799.

Scorrano, M., Giansoldati, M., & Andreas Mathisen, T. (2019). Is electric car uptake driven by monetary factors? A total cost of ownership comparison between Norway and Italy. *Economic and Policy of Energy and The Environment, 2*, 99-132.

She, Z. Y., Sun, Q., Ma, J. J., & Xie, B. C. (2017). What are the barriers to widespread adoption of battery electric vehicles? A survey of public perception in Tianjin, China. *Transport Policy, 56*, 29-40.

Sheldon, T. L., DeShazo, J. R., & Carson, R. T. (2017). Electric and plug-in hybrid vehicle demand: lessons for an emerging market. *Economic Inquiry, 55*(2), 695-713.

Shin, J., Lim, T., Kim, M. Y., & Choi, J. Y. (2018). Can next-generation vehicles sustainably survive in the automobile market? Evidence from ex-ante market simulation and segmentation. *Sustainability, 10*(3), 607.

Singh, V., Singh, V., & Vaibhav, S. (2020). A review and simple meta-analysis of factors influencing adoption of electric vehicles. *Transportation Research Part D: Transport and Environment, 86*, 102436.

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

Sottile, E., Meloni, I., & Cherchi, E. (2017). Hybrid choice model to disentangle the effect of awareness from attitudes: Application test of soft measures in medium size city. *Case Studies on Transport Policy, 5*(2), 400-407.

Sovacool, B. K., Abrahamse, W., Zhang, L., & Ren, J. (2019). Pleasure or profit? Surveying the purchasing intentions of potential electric vehicle adopters in China. *Transportation Research Part A: Policy and Practice, 124*, 69-81.

Squazzoni, F. (2010). The impact of agent-based models in the social sciences after 15 years of incursion. *History of Economic Ideas, 18*(2), 197-234.

Sun, X., Liu, X., Wang, Y., & Yuan, F. (2019). The effects of public subsidies on emerging industry: An agent-based model of the electric vehicle industry. *Technological Forecasting and Social Change, 140*, 281-295.

Tabachnick, B. G., Fidell, L. S., & Ullman, J. B. (2007). *Using multivariate statistics* (Vol. 5). Boston: Pearson Boston, MA.

Tavakol, M., & Dennick, R. (2011). Making sense of Cronbach's alpha. *International journal of medical education, 2*, 53.

Tchetchik, A., Zvi, L. I., Kaplan, S., & Blass, V. (2020). The joint effects of driving hedonism and trialability on the choice between internal combustion engine, hybrid, and electric vehicles. *Technological Forecasting and Social Change, 151*, 119815.

Ten Have, S. Y., Gkiotsalitis, K., & Geurs, K. T. (2020). Investigating the future of ultrafast charging: A choice experiment in The Netherlands. *World Electric Vehicle Journal, 11*(4), 70.

Thies, C., Kieckhäfer, K., & Spengler, T. S. (2016). Market introduction strategies for alternative powertrains in long-range passenger cars under competition. *Transportation Research Part D: Transport and Environment, 45*, 4-27.

Thompson, B. (2004). Exploratory and confirmatory factor analysis: Understanding concepts and applications. *Applied Psychological Measurement, 31*(3), 245-248.

Train, K. E. (2009). *Discrete choice methods with simulation*: Cambridge university press.

UNRAE. (2022). La struttura del mercato italiano dell'automobile - Immatricolazioni (Dicembre 2021). from Unione Nazionale Rappresentanti Autoveicoli Esteri (UNRAE) http://www.unrae.it

UNRAE. (2023). Market Structure-December 2022. from Unione Nazionale Rappresentanti Autoveicoli Esteri (UNRAE) http://www.unrae.it/

Vilchez, J. J. G., & Jochem, P. (2019). Simulating vehicle fleet composition: A review of system dynamics models. *Renewable and Sustainable Energy Reviews, 115*, 109367.

Wang, Y., Yao, E., & Pan, L. (2021). Electric vehicle drivers' charging behavior analysis considering heterogeneity and satisfaction. *Journal of Cleaner Production, 286*. doi: 10.1016/j.jclepro.2020.124982

Watkins, M. W. (2018). Exploratory factor analysis: A guide to best practice. *Journal of Black Psychology, 44*(3), 219-246.

Williams, B., Onsman, A., & Brown, T. (2010). Exploratory factor analysis: A five-step guide for novices. *Australasian journal of paramedicine, 8*, 1-13.

Wolbertus, R., & Gerzon, B. (2018). Improving electric vehicle charging station efficiency through pricing. *Journal of Advanced Transportation, 2018*, 4831951.

Wolf, I., Schröder, T., Neumann, J., & de Haan, G. (2015). Changing minds about electric cars: An empirically grounded agent-based modeling approach. *Technological Forecasting and Social Change, 94*, 269-285.

Yang, C. W., & Ho, Y. L. (2016). Assessing carbon reduction effects toward the mode shift of green transportation system. *Journal of Advanced Transportation, 50*(5), 669-682.

Yang, D., & Timmermans, H. (2017). Households transport-home energy conservation strategies in response to energy price policies: A stated adaptation experiment based on portfolio choices and cross effects designs. *International Journal of Sustainable Transportation, 11*(2), 133-147.

Yang, S., Cheng, P., Li, J., & Wang, S. (2019). Which group should policies target? Effects of incentive policies and product cognitions for electric vehicle adoption among Chinese consumers. *Energy Policy, 135*, 111009.

Yang, W., Xiang, Y., Liu, J., & Gu, C. (2017). Agent-based modeling for scale evolution of plug-in electric vehicles and charging demand. *IEEE Transactions on Power Systems, 33*(2), 1915-1925.

Yang, W., Zhou, H., Liu, J., Dai, S., Ma, Z., & Liu, Y. (2015). *Market evolution modeling for electric vehicles based on system dynamics and* *multi-agents*. Paper presented at the 2015 International Symposium on Smart Electric Distribution Systems and Technologies (EDST).

Yang, X., Jin, W., Jiang, H., Xie, Q., Shen, W., & Han, W. (2017). Car ownership policies in China: Preferences of residents and influence on the choice of electric cars. *Transport Policy, 58*, 62-71.

Yang, Y., Yao, E., Yang, Z., & Zhang, R. (2016). Modeling the charging and route choice behavior of BEV drivers. *Transportation Research Part C: Emerging Technologies, 65*, 190-204.

Yong, A. G., & Pearce, S. (2013). A beginner's guide to factor analysis: Focusing on exploratory factor analysis. *Tutorials in quantitative methods for psychology, 9*(2), 79-94.

Zhang, H., & Vorobeychik, Y. (2019). Empirically grounded agent-based models of innovation diffusion: a critical review. *Artificial Intelligence Review, 52*(1), 707-741.

Zhang, X., Bai, X., & Shang, J. (2018). Is subsidized electric vehicles adoption sustainable: Consumers' perceptions and motivation toward incentive policies, environmental benefits, and risks. *Journal of Cleaner Production, 192*, 71-79.

Zhou, Y., Wen, R., Wang, H., & Cai, H. (2020). Optimal battery electric vehicles range: A study considering heterogeneous travel patterns, charging behaviors, and access to charging infrastructure. *Energy, 197*, 116945.

Zhu, C., Zhu, Y., Lu, R., He, R., & Xia, Z. (2012). Perceptions and aspirations for car ownership among Chinese students attending two universities in the Yangtze Delta, China. *Journal of Transport Geography, 24*, 315-323.

Zhuge, C., Wei, B., Dong, C., Shao, C., & Shan, Y. (2019). Exploring the future electric vehicle market and its impacts with an agent-based spatial integrated framework: A case study of Beijing, China. *Journal of Cleaner Production, 221*, 710-737.

Zhuge, C., Wei, B., Shao, C., Dong, C., Meng, M., & Zhang, J. (2020). The potential influence of cost-related factors on the adoption of electric vehicle: An integrated micro-simulation approach. *Journal of Cleaner Production, 250*, 119479.

Zhuge, C., Wei, B., Shao, C., Shan, Y., & Dong, C. (2020). The role of the license plate lottery policy in the adoption of Electric Vehicles: A case study of Beijing. *Energy Policy, 139*, 111328.

Appendix A : Market Distribution in Italy and China

Table A 1 The market distribution in Italy (2020)

Propulsion system	Model type	11/2020	11/2019
CNG	FIAT PANDA	4,699	8,933
	VOLKSWAGEN T-CROSS	2,791	2,791
	CITROEN C3	2,622	2,622
	PEUGEOT 208	1,781	1,781
	JEEP RENEGADE	1,662	1,662
	Total number	43,533	43,533
	Percentage	31.1%	45.7%
Diesel	JEEP COMPASS	2,353	1,952
	FIAT 500X	1,918	2,293
	NISSAN QASHQAI	1,809	1,287
	JEEP RENEGADE	1,292	1,520
	PEUGEOT 3008	1,258	2,338
	Total number	40,395	56.438
	Percentage	28.9%	37%
HEV	FIAT PANDA	5,448	0
	TOYOTA YARIS	4,037	1,793
	LANCIA YPSILON	3,406	0
	FIAT 500	3,293	0
	FORD PUMA	1,864	0
	Total number	32,309	10,536
	Percentage	23.1%	6.9%
LPG	DACIA SANDERO	3,021	48
	RENAULT CAPTUR	2,000	0
	DACIA DUSTER	1,672	2,441
	RENAULT CLIO	1,096	46
	FIAT PANDA	552	1,542
	Total number	11,124	9,730
	Percentage	8.0%	6.4%
CNG	SKODA KAMIQ	499	0
	SEAT ARONA	466	552
	VOLKSWAGEN UP!	352	585
	VOLKSWAGEN POLO	332	312
	VOLKSWAGEN GOLF	251	1,006
	Total number	2,795	4,040
	Percentage	2.0%	2.7%
PHEV	JEEP COMPASS	923	0
	RENAULT CAPTUR	864	0
	MERCEDES CLASSE A	359	0
	JEEP RENEGADE	344	0
	VOLVO XC40	232	0
	Total number	4.940	982
	Percentage	3.5%	0.6%
BEV	VOLKSWAGEN UP!	657	0
	SMART FORTWO	558	426
	RENAULT ZOE	554	254
	FIAT 500	513	0
	RENAULT TWINGO	411	0
	Total number	4,810	1,068
	Percentage	3.4%	0.7%

Table A 2 The market distribution in China (2020)

	Vehicle types	Price(¥)	Fuel tank capacity (L)	Fuel economy(L/100km)	Driving range(Km)	10/2020	10/2019
BEV	Wuling Sunshine MINI EV	28,800	\	\	120	23762	0
	Tesla Model 3	247,200	\	\	468	12143	0
	Ora R1	69,800	\	\	301	6269	1618
	BYD Han EV	207,300	\	\	605	5055	0
	Chery eQ1	59,800	\	\	301	4745	2414
	Total number					109,562	46,483
	Percentage					5.50%	2.52%
PHEV	BYD Tang DM	228,300	53	1.8	2944	3721	2016
	BYD Han DM	211,300	48	1.4	3429	2490	0
	BMW 535Le PHEV	499,900	46	1.5	3067	2205	2764
	ROEWE RX5	147,300	37	1.6	2313	1625	357
	Volkswagen Passat	235,400	50	1.6	3125	1173	597
	Total number					23,583	16,545
	Percentage					1.18%	0.9%
CNG	Nissan Sylphy	99,800	50	6.1	820	56201	43031
	Havel H6	98,000	58	6.9	840	52734	23692
	Volkswagen Lavida	99,000	52.8	5.7	926	40984	41429
	Volkswagen Bora	98,800	55	5.8	948	37944	29735
	Volkswagen Sagitar	128,900	50	5.7	877	36380	32784
	Total number					1,832,636	1,679,702
	Percentage					93.6%	97%
Diesel	Beijing BJ40	159,900	75	798	798	1680	1516
	Maxus G10	163,800	75	962	962	745	1134
	Maxus G20	199,800	72	923	923	470	390
	JAC Refine M4	138,800	75	949	949	466	912
	JMC Yusheng S350	137,600	68	944	944	105	113
	Total number				798	3606	4627
	Percentage					0.2%	0.3%
HEV	HONDA Accord	179,800	48.5	4.2	1155	\	\
	Honda CR-V 2.0	209,800	53	4.9	1082	\	\
	TOYOTA Camry	239,800	49	4.1	1195	\	\
	TOYOTA Corolla	135,800	43	4	1075	\	\
	LEXUS ES 300h	374,000	49.3	4.2	1174	\	\
	Total number					22,401	17,244
	Percentage					1.1%	0.9%

Brand: FIAT 500
Propulsion system: BEV
Purchase price: €18,150
Driving range: 320 km

Brand: Citroen C3
Propulsion system: Petrol
Purchase price: €14,100
Driving range: 1071 km

Brand: FIAT 500X
Propulsion system: Diesel
Purchase price: €21,500
Driving range: 1310 km

Brand: Dacia Duster
Propulsion system: LPG
Purchase price: €14,850
Driving range: 625 km

Brand: Volkswagen Polo
Propulsion system: CNG
Purchase price: €19,500
Driving range: 400 km

Brand: Fiat Panda
Propulsion system: HEV
Purchase price: €11,000
Driving range: 974km

Brand: Jeep Compass 4XE
Propulsion system: PHEV
Purchase price: €33,450
Driving range: 1015 km

Figure 9 The BEV of Fiat 500e model in Italy

Brand:BYD Han EV
Propulsion system:BEV
Purchase price: ¥209,800
Driving range: 506 km

Brand: Nissan Sylphy
Propulsion system: Petrol
Purchase price: ¥ 120,000
Driving range: 886 km

Brand: Beijing BJ40
Propulsion system:Diesel
Purchase price: ¥ 160,000
Driving range:798 km

Brand: Honda Accord
Propulsion system:HEV
Purchase price: ¥ 180,000
Driving range:875 km

Brand: BYD Qin Plus
Propulsion system:PHEV
Purchase price: ¥107,800
Driving range:1180 km

Figure 10 The BEV of BYD Han EV in China

Appendix B : Statistic Code in R

1 Ngene code

- **Instruction code for Italian sample part:**

;alts = P,D, LPG,CNG,BEV, HEV,PHEV

** The alternatives (alts) are considered as: CNG cars (P), Diesel cars (D), Liquefied CNGeum Gas Vehicles (LPG), Compressed Natural Gas Vehicles (CNG), Battery Electric Vehicles (BEVs), Plug-in Hybrid Electric Vehicles (PHEVs) and Hybrid Electric Vehicles (HEVs)

;rows = 40

** 40 choice scenarios in Italy

;eff=(mnl,d)

** Estimated with MNL model, the measurement method is used D-error

;model:

U(P)=bprice[-0.11605]*price_p[10,12,14,16,18]+brange_ICE[0.0009]*range_p[700, 850, 1000]/

U(D)= bprice*price_d[13,16,19,21,24]+brange_ICE*range_d[800, 1000, 1300]/

U(LPG)=bprice*price_lpg[12,14,16,18,20]+brange_ICE*range_lpg[500, 700, 900]/

U(CNG)=bprice*price_cng[15,18,20,23,25]+brange_ICE*range_cng[300, 600, 900]/

U(BEV)=bprice*price_bev[18,22,26,30,34]+brange_BEV[0.00333]*range_bev[200, 300, 400]/

U(HEV)=bprice*price_hev[14,17,20,23,26]+brange_ICE*range_hev[900,1100,1300]/

U(PHEV)=bprice*price_phev[22,25,28,31,34]+brange_ICE*range_phev[800,1000, 1300]

$

** In the MNL utility function, “bprice” and “brange_ICE” are the general parameters, the coefficience of price [-0.11605] and driving range [0.0009] of ICE vehicles are the prior value which we get from a survey in Italy (Danielis et al., 2020), the coefficience of driving range[0.00333] of is the prior value got from Chinese market in (Qian et al., 2019). The price data which listed in bracket (such as [10,12,14,16,18])is the data what we have get in real car market in Italy, it is calculated as per thousand euro. The same express for driving range.

Instruction code for Chinese sample part:

;alts = P,D,BEV, HEV,PHEV

;rows = 30

;eff=(mnl,d)

;model:

U(P)=bprice[-0.055]*price_p[90,110,130,150,170]+brange_ICE[0.002]*range_p[700,850,1000]/

U(D)=bprice*price_d[120,140,160,180,200] + brange_ICE*range_d[800,1000,1300]/

U(BEV)=bprice*price_bev[90,130,150,200,250]+brange_BEV[0.003]*range_bev[400,500,600]/

U(PHEV)=bprice*price_phev[130,160,180,220,250]+ brange_ICE*range_phev[800, 1000, 1300]/

U(HEV)=bprice*price_hev[110,130,150,170,200]+brange_ICE*range_hev[900,1100,1300]

$

2 Estimation in R (MNL)

- Normorlized parameter code in R

Clear the memory/workspace

rm(list = ls())

Load Apollo library

library(apollo)

Initialise code

apollo_initialise()

Set core controls

apollo_control = list(modelName ="Results_24_04_2021", modelDescr ="MNL on data without socioeconomics 24_04_2021", indivID ="ID")

Load data and apply any transformations

database = read.csv("Database for R_Italy_14_04_2021.csv",sep=",",header=TRUE)

database = subset(database,database$SP==1)

Vector of parameters, including any that are kept fixed in estimation

*** Define the parameters and starting values, and fixed some of the parameters to starting values.

```
apollo_beta=c( asc_petrol_cn = 0,
               asc_diesel_cn = 0,
               asc_bev_cn = 0,
               asc_hev_cn = 0,
               asc_phev_cn = 0,
               b_price_cn = 0,
               b_range_ice_cn = 0,
               b_range_bev_cn = 0,

               asc_petrol_it = 0,
               asc_diesel_it = 0,
               asc_lpg_it = 0,
               asc_cng_it = 0,
               asc_bev_it = 0,
               asc_hev_it = 0,
               asc_phev_it = 0,
               b_price_it = 0,
               b_range_ice_it = 0,
               b_range_bev_it = 0,

               lambda = 1
               )
```

Vector with names (in quotes) of parameters to be kept fixed at their starting

###value in apollo_beta, use apollo_beta_fixed = c() if none

apollo_fixed = c("asc_CNG_it","asc_CNG_cn")

GROUP AND VALIDATE INPUTS

apollo_inputs = apollo_validateInputs()
DEFINE MODEL AND LIKELIHOOD FUNCTION
apollo_probabilities=function(apollo_beta, apollo_inputs, functionality="estimate"){
Attach inputs and detach after function exit
apollo_attach(apollo_beta,
apollo_inputs)
*** Enable users to call individual elements in the database by name, but it cannot return an object as output, users do not need to change any arguments
on.exit(apollo_detach(apollo_beta, apollo_inputs))
*** Eun the function *apollo_detach* once the code exits *apollo_probabilities*
Create list of probabilities P
P = list()
List of utilities: these must use the same names as in mnl_settings, order is irrelevant
V = list()
*** V is the utility function of MNL model, included the alternative specific constants(ASCs), purchase price and driving range, excluded the error term.
*** Lambda is a scale parameter, to be equal to the ratio of the standard deviations.
V[['petrol_it']] = asc_petrol_it + b_price_it * Price_p_it + b_range_ice_it * Range_p_it
V[['diesel_it']] = asc_diesel_it + b_price_it * Price_d_it + b_range_ice_it * Range_d_it
V[['lpg_it']] = asc_lpg_it + b_price_it * Price_lpg_it + b_range_ice_it * Range_lpg_it
V[['cng_it']] = asc_cng_it + b_price_it * Price_cng_it + b_range_ice_it * Range_cng_it
V[['bev_it']] = asc_bev_it + b_price_it * Price_bev_it + b_range_bev_it * Range_bev_it
V[['hev_it']] = asc_hev_it + b_price_it * Price_hev_it + b_range_ice_it * Range_hev_it
V[['phev_it']] = asc_phev_it + b_price_it * Price_phev_it + b_range_ice_it * Range_phev_it

V[['petrol_cn']] = lambda*(asc_petrol_cn + b_price_cn * Price_p + b_range_ice_cn * Range_p)
V[['diesel_cn']] = lambda*(asc_diesel_cn + b_price_cn * Price_d + b_range_ice_cn * Range_d)
V[['bev_cn']] = lambda*(asc_bev_cn + b_price_cn * Price_bev + b_range_bev_cn * Range_bev)
V[['hev_cn']] = lambda*(asc_hev_cn + b_price_cn * Price_hev + b_range_ice_cn * Range_hev)
V[['phev_cn']] = lambda*(asc_phev_cn + b_price_cn * Price_phev + b_range_ice_cn * Range_phev)
Define settings for MNL model component
mnl_settings = list(alternatives = c(CNG_it=1, diesel_it=2, lpg_it=3, cng_it=4, bev_it=5, hev_it=6, phev_it=7, CNG_cn=8, diesel_cn=9, bev_cn=10, hev_cn=11, phev_cn=12),
***For each alternative, set the value used in dependent variable in the data, the value is from 1 to 12
avail = list(CNG_it=av_CNG_it, diesel_it=av_diesel_it, lpg_it = av_lpg_it, cng_it = av_cng_it,bev_it=av_bev_it, hev_it=av_hev_it, phev_it=av_phev_it, CNG_cn=av_CNG_cn, diesel_cn=av_diesel_cn, bev_cn=av_bev_cn, hev_cn=av_hev_cn, phev_cn=av_phev_cn),
***Avail means a list contained one element per alternative, set the same names as in alternatives
choiceVar = Choice_2,

******* choiceVar is a vetor contained all the chosen alternatives for each observation, the name in our sample is Choice_2

V = V

)

Compute probabilities using MNL model

P[['model']] = apollo_mnl(mnl_settings, functionality)

Take product across observation for same individual

P = apollo_panelProd(P, apollo_inputs, functionality)

Prepare and return outputs of function

P = apollo_prepareProb(P, apollo_inputs, functionality)

return(P)

}

MODEL ESTIMATION

model = apollo_estimate(apollo_beta, apollo_fixed, apollo_probabilities, apollo_inputs)

MODEL OUTPUTS

##FORMATTED OUTPUT (TO SCREEN)

apollo_modelOutput(model, modelOutput_settings=list(printPVal=2))

*** printPVal: If set to 0, p-values are not reported. If set to 1, one-sided p-values are reported. If set to 2, two-sided p-values are reported

###FORMATTED OUTPUT (TO FILE, using model name)

apollo_saveOutput(model, list(printPVal = 2)

3 Estimation in R (MXL)

```
#######LOAD LIBRARY AND DEFINE CORE SETTINGS#######
rm(list = ls())

### Load Apollo library
library(apollo)

### Initialise code
apollo_initialise()

### Set core controls
apollo_control = list(
      modelName ="Model application 30_09_2022(draws500)",
      modelDescr ="Mixed logit model on IT and CN data, correlated Lognormals in utility space, individual heterogeneity",
      indivID    ="ID",
      mixing     = TRUE,
      nCores     = 4
)

#######LOAD DATA AND APPLY ANY TRANSFORMATION#######
database = read.csv("09_12_2021_Data for R_IT and CN.csv",header=TRUE)
database = subset(database,database$SP==1)

#######DEFINE MODEL PARAMETERS#######
### Vector of parameters, including any that are kept fixed in estimation
apollo_beta = c(
                 asc_petrol_it        = 0,
                 asc_diesel_it        = 0,
                 asc_lpg_it           = 0,
                 asc_cng_it           = 0,
                 # asc_bev_it         = 0,
                 mu_asc_bev_it        = 0,
                 sigma_asc_bev_it     = 0,

                 asc_hev_it           = 0,
                 asc_phev_it          = 0,
                 mu_b_price           = 0,
                 sigma_b_price        = 0,
                 mu_b_range_ice_it    = 0,
                 sigma_b_range_ice_it = 0,
                 mu_b_range_bev_it    = 0,
```

sigma_b_range_bev_it = 0,

asc_petrol_cn = 0,
asc_diesel_cn = 0,
#asc_bev_cn = 0,
mu_asc_bev_cn = 0,
sigma_asc_bev_cn = 0,

asc_hev_cn = 0,
asc_phev_cn = 0,

mu_b_range_ice_cn = 0,
sigma_b_range_ice_cn = 0,
mu_b_range_bev_cn = 0,
sigma_b_range_bev_cn = 0,

lambda = 1
)

Vector with names (in quotes) of parameters to be kept fixed at their starting value in apollo_beta, use apollo_beta_fixed = c() if none apollo_fixed = c("asc_petrol_it","asc_petrol_cn")
####### DEFINE RANDOM COMPONENTS#######
Set parameters for generating draws
apollo_draws = list(
interDrawsType = "halton",
interNDraws = 500,
interUnifDraws = c(),
interNormDraws=c("draws_price","draws_range", "draws_asc_bev"),
intraDrawsType = "halton",
intraNDraws = 0,
intraUnifDraws = c(),
intraNormDraws = c()
)
Create random parameters
apollo_randCoeff = function(apollo_beta, apollo_inputs){
randcoeff = list()
randcoeff[["asc_bev_it"]]=(mu_asc_bev_it+igma_asc_bev_it*draws_asc_bev)
randcoeff[["asc_bev_cn"]]=(mu_asc_bev_cn+sigma_asc_bev_cn*draws_asc_bev)
randcoeff[["b_price"]] =(mu_b_price + sigma_b_price*draws_price)

randcoeff[["b_range_ice_it"]]=(mu_b_range_ice_it+sigma_b_range_ice_it*draws_range)
randcoeff[["b_range_bev_it"]]=(mu_b_range_bev_it+sigma_b_range_bev_it*draws_range)

randcoeff[["b_range_ice_cn"]]=(mu_b_range_ice_cn+sigma_b_range_ice_cn*draws_range)
randcoeff[["b_range_bev_cn"]]=(mu_b_range_bev_cn+sigma_b_range_bev_cn*draws_range)

return(randcoeff)
}

#####GROUP AND VALIDATE INPUTS######

apollo_inputs = apollo_validateInputs()

####DEFINE MODEL AND LIKELIHOOD FUNCTION######

apollo_probabilities=function(apollo_beta, apollo_inputs, functionality="estimate"){

Function initialisation: do not change the following three commands

Attach inputs and detach after function exit

apollo_attach(apollo_beta, apollo_inputs)
on.exit(apollo_detach(apollo_beta, apollo_inputs))

Create list of probabilities P

P = list()

List of utilities: these must use the same names as in mnl_settings, order is irrelevant###

V = list()
V[['petrol_it']] = asc_petrol_it + b_price * Price_p + b_range_ice_it * Range_p
V[['diesel_it']] = asc_diesel_it + b_price * Price_d + b_range_ice_it * Range_d
V[['lpg_it']] = asc_lpg_it + b_price * Price_lpg + b_range_ice_it * Range_lpg
V[['cng_it']] = asc_cng_it + b_price * Price_cng + b_range_ice_it * Range_cng
V[['bev_it']] = asc_bev_it + b_price * Price_bev + b_range_bev_it * Range_bev
V[['hev_it']] = asc_hev_it + b_price * Price_hev + b_range_ice_it * Range_hev
V[['phev_it']] = asc_phev_it + b_price * Price_phev + b_range_ice_it * Range_phev

V[['petrol_cn']] = lambda*(asc_petrol_cn + b_price * Price_p + b_range_ice_cn* Range_p)
V[['diesel_cn']] = lambda*(asc_diesel_cn + b_price * Price_d + b_range_ice_cn * Range_d)
V[['bev_cn']] = lambda*(asc_bev_cn + b_price * Price_bev + b_range_bev_cn* Range_bev)

V[['hev_cn']] = lambda*(asc_hev_cn + b_price * Price_hev + b_range_ice_cn * Range_hev)
V[['phev_cn']] = lambda*(asc_phev_cn + b_price * Price_phev + b_range_ice_cn * Range_phev)
Define settings for MNL model component###
mnl_settings = list(
alternatives = c(petrol_it=1, diesel_it=2, lpg_it = 3 , cng_it = 4, bev_it=5, hev_it=6, phev_it=7,petrol_cn=8, diesel_cn=9, bev_cn=10, hev_cn=11, phev_cn=12),

avail = list (petrol_it = av_petrol_it, diesel_it = av_diesel_it, lpg_it = av_lpg_it, cng_it = av_cng_it,bev_it = av_bev_it, hev_it = av_hev_it, phev_it = av_phev_it, petrol_cn = av_petrol_cn, diesel_cn = av_diesel_cn, bev_cn = av_bev_cn, hev_cn = av_hev_cn, phev_cn = av_phev_cn),

choiceVar = CHOICE,
V = V
)
Compute probabilities using MNL model
P[['model']] = apollo_mnl(mnl_settings, functionality)
Take product across observation for same individual
P = apollo_panelProd(P, apollo_inputs, functionality)
Average across inter-individual draws
P = apollo_avgInterDraws(P, apollo_inputs, functionality)
Prepare and return outputs of function
P = apollo_prepareProb(P, apollo_inputs, functionality)
return(P)
}
####MODELESTIMATION###
model=apollo_estimate(apollo_beta,apollo_fixed,apollo_probabilities,apollo_inputs)

###MODEL OUTPUTS #####
apollo_modelOutput(model, modelOutput_settings=list(printPVal=2))
apollo_saveOutput(model, list(printPVal = 2))

Use the estimated model to make predictions
predictions_base = apollo_prediction(model, apollo_probabilities, apollo_inputs)
summary(predictions_base)

Now imagine the price of EV decreases by 20%
database$Price_bev = 0.8*database$Price_bev
apollo_inputs=apollo_validateInputs()

```
### Rerun predictions with the new data
predictions_new = apollo_prediction(model, apollo_probabilities, apollo_inputs)
summary(predictions_new)

### Return to original data
database$Price_bev = 1/0.8*database$Price_bev

### Now imagine the range of EV increases by 50%
database$Range_bev = 1.5*database$Range_bev
apollo_inputs=apollo_validateInputs()

### Rerun predictions with the new data
predictions_new = apollo_prediction(model, apollo_probabilities, apollo_inputs)
summary(predictions_new)
### Return to original data
database$Range_bev = 1/1.5*database$Range_bev
### Now imagine the price of EV decreases by 20% AND the range of EV increases by 50%###
database$Price_bev = 0.8*database$Price_bev
database$Range_bev = 1.5*database$Range_bev
apollo_inputs=apollo_validateInputs()
predictions_new = apollo_prediction(model, apollo_probabilities, apollo_inputs)
summary(predictions_new)

### Return to original data
database$Price_bev = 1/0.8*database$Price_bev
database$Range_bev = 1/1.5*database$Range_bev
```

Appendix C : Pre-test Experiment

1 Pre-test data descriptive

Data collection for Italy and China

The survey was carried out by web-based version in Italy and China separately. The data collection in Italy was conducted through Google form while the collection conducted in China relied on the Chinese marketing research company “Sojump” (http://www.sojump.com). The data collection was carried out twice for the Italian sample (N=21) and for the Chinese sample (N=20) by using a CAWI (Computer Assisted Web Interviewing) questionnaire during December 2020.

The questionnaires were randomly provided to respondents. The groups of our respondents are same across both times. In order to confirm whether the respondents’ stated preference was influenced by their initial impression or not, we have change the order of net purchase price and driving range in the scenarios. Then we carried out the survey on the same group. The results of the two times listed in Table 34 are almost the same, confirming that the sequence of price and driving range would not significantly influence the preferences of respondents, so we would use the results of the first time.

Table 34 Results for Pre-test for Two times

	Italy				China			
	First time		Second time		First time		Second time	
	Estimate	t.ratio	Estimate	t.ratio	Estimate	t.ratio	Estimate	t.ratio
asc_petrol	0	NA	0	NA	0	NA	0	NA
asc_diesel	0.3775	1.6500	0.4567**	1.9	-1.5851***	-6.5590	-1.3718***	-5.3990
asc_lpg	-0.4992**	-1.9200	-0.7082***	-2.62	/	/	/	/
asc_cng	-1.4179**	-1.9300	-10.8758	-0.13	/	/	/	/
asc_bev	3.3179*	1.7500	4.1655**	2.19	2.3554***	2.3420	2.4266**	1.9990
asc_hev	1.2087***	5.0200	1.5304***	5.94	-0.6872***	-3.6750	-0.5430***	-2.6800
asc_phev	0.6301	1.4700	0.2743*	0.49	-0.4440**	-2.1420	-0.9799***	-3.7320
b_price	-0.2642***	-12.6400	-0.3219***	-13.79	-0.0114***	-5.6360	-0.0167***	-6.5500
b_range_ice	0.0032***	7.5500	0.0028***	6	0.0020***	5.2480	0.0026***	6.1630
b_range_bev	-0.0006	-0.1200	-0.0032	-0.66	-0.0026*	-1.4170	-0.0022	-1.0060

Notes: *Statistical significance at the 10% level, **Statistical significance at the 5% level, ***Statistical significance at the 1% level or smaller.

Pre-test sample description

Table 35 lists descriptive statistics of socio-economic characteristics. We have collected 21 samples in Italy and 20 samples in China, nearly the same proportion of samples in each country.

There are some similaries in both two countries. For the income level, there is no remarkable difference between Italy and China, although the real annual household income is much higher in Italy. For the proximity of fast charging station, more than half of the respondents in both countries cannot have a fast charging infrastructure near their workplace.

As to the gender distribution, the proportion of males in the Italian sample was higher than that of in the Chinese sample. The age group in the Italian sample was concentrated on the older group (47% of 35 years old or older), while the largest group in the Chinese sample was on the younger group (90% of 35 years old or younger). In terms of education levels, the Italian sample covered all the education levels, but the share of respondents with postgraduate level was higher. All the Chinese respondents have a university degree or above.

Moreover, the main difference concerns the garage availability of respondents. The people who have a garage for their charging in Italy is much higher. In terms of car ownership, there was also a significant difference, more than two thirds of the Italian families has owned more than two cars, while there is only three quarters of the Chinese respondents owned less than two cars. In terms of family structure, small family structure composed of three members was common in Italy, while in China there were large families with four or more members. In terms of city size, the majority Italians lived in small city and rural areas, while most Chinese respondents lived in large cities. Table 36 lists the characteristics of revealed preference in Italy and China. It can be seen that distributions for purchasing years were significant different. In Italy, all of the respondents have their owned cars; moreover, all of the cars were bought before 2010 and they were all petrol cars (29%), whereas, in China, 15% of the respondents did not own a car, all of the ones were bought after 2010. In terms of propulsion system, almost half of the bought ones were diesel cars in Italy, while respondents in China were more preferred petrol cars. The summarized main differences between the Italian and Chinese sample are listed as follows.

- Garage availability: 71% of respondents in Italy have a garage or parking place for charging, while there were only half of the Chinese respondents owning a garage or parking place for charging (55%).
- Car ownership: More than two thirds of the Italian families (71%) owned two or more cars, while three quarters Chinese respondents owned just one or no cars (80%).
- Type of purchased or used car: most of the cars of the Italian respondents are in the small or medium segments, while the Chinese ones preferred the medium and large segments.

Table 35 Descriptive statistic of Pre-test

	Italy	China
Socio economic information		
Respondents number	21(51%)	20(49%)
Gender	Male: 14 (67%), Female: 7 (33%)	Male: 9 (45%), Female: 11 (55%)
Age	18-25: 5(24%), 26-35: 6(29%), 36-45: 2(9%), 46-55: 3(14%), 56-65: 5(24%)	18-25: 0, 26-35: 18(90%), 36-45: 2(10%), 46-55: 0, 56-65: 0
Education Level	Post Graduate: 9(43%), Master: 4(19%), Bachelor: 4(19%), High school diploma: 2(9%), Professional degree: 1(5%), Junior high school license: 1(5%), Primary school: 0	Post Graduate: 3(15%), Master:8(40%), Bachelor: 9(45%), High school diploma:0, Professional degree: 0, Junior high school license:0, Primary school: 0
Current Job	Entrepreneur: 1(5%), Executive employee: 1(5%), White collar: 1(5%), Looking for first occupation: 0, Student: 8(38%), Unemployed-looking for a new job: 0, Engaged in own household: 0, Retired: 1(5%), Other: 9(42%)	Entrepreneur: 0, Executive employee: 5(25%), White collar:11(55%), Looking for first occupation: 0, Student: 0, Unemploye－looking for a new job: 0, Engaged in own household: 0, Retired: 0, Other: 4(20%)
Family annual income	less than €30,000: 6(29%), between €30,000 and €70,000: 13(62%), more than €70,000: 2(9%)	less than ¥30,000:0, between ¥30,000 and ¥60,000:1(5%), more than ¥60,000:19(95%)
Family members	1: 2(9%), 2: 5(24%), 3: 8(38%), 4: 5(24%), 5: 1(5%), More than 5: 0	1:0, 2: 5(25%), 3: 4(20%), 4: 6(30%), 5: 5(25%), More than 5: 0
Location		
City size	Large city (from 250 thousand to 1 million inhabitants): 1(5%), Small or medium town (less than 250 thousand inhabitants): 15(71%), Rural area: 5(24%)	Super cities (more than 10 million inhabitants): 7(35%), Very large cities (more than 5 million and less than 10 million inhabitants): 8(40%), Large cities (more than 1 million and less than 5 million inhabitants): 1(5%), Medium cities (more than 500 thousand and less than 1 million inhabitants): 3(15%), Small cities (less than 500 thousand inhabitants): 1(5%), Rural areas: 0
Living area	Detached house with a garage or private parking space: 8(38%), Detached house without a garage or private parking space: 1(5%), Apartment with garage or private parking space: 7(33%), Apartment without garage or private parking space: 5(24%)	Detached house with a garage or private parking space: 1(5%), Detached house without a garage or private parking space: 1(5%), Apartment with garage or private parking space:10(50%), Apartment without garage or private parking space: 8(40%)
Car and garage ownership		
Garage recharging availability	Yes: 10(48%), No: 11(52%)	Yes: 9(45%), No: 11(55%)
Car numbers in the household	0: 4(19%), 1: 2(10%), 2: 11(52%), 3: 4(19%)	0:1(5%), 1:15(75%), 2: 2(10%), 3: 2(10%)
Car mobility habits:		
Driving distance per day	⩽ 20 km: 5(24%), 20-50km: 3(14%), 50~80 km: 3(14%), 80~100 km: 0, ⩾ 100 km: 0, I don't regularly drive a car: 10(48%)	⩽ 20 km: 8(40%), 20-50km: 5(25%), 50~80 km: 1(5%), 80~100 km: 1(5%), ⩾ 100 km: 1(5%), I don't regularly drive a car: 4(20%)
Driving distance in the last 12 months	⩽ 5,000 km: 15(70%), 5001–10,000 km: 2(10%), 10,001–20,000 km: 2(10%), 20,001–50,000 km: 2(10%), >50,000 km: 0	⩽ 5,000 km: 13(65%), 5001–10,000 km: 2(10%), 10,001–20,000 km: 2(10%), 20,001–50,000 km: 2(10%), >50,000 km:1(5%)
Distance between home-work/education place:	⩽ 20 km: 12(57%), 20-50km: 3(14%), 50~80 km: 2(10%), 80~100 km: 1(5%), ⩾ 100 km: 3(14%)	⩽ 20 km: 10(50%), 20-50km: 6(30%), 50~80 km: 2(10%), 80~100 km: 0, ⩾ 100 km: 2(10%)
Proximity to fast charging stations:	Yes: 9(43%), No: 4(19%), I don't know: 8(38%)	Yes: 9(45%), No: 1(5%), I don't know: 10(50%)

Table 36 Revealed Preference in Italy and China sample

Revealed preferences		
Purchase Year:	Before 2000 year: 4(19%), 2001-2010 year: 2(10%), After 2010 year: 15(71%), None: 0	Before 2000 year: 0, 2001-2010 year: 0, After 2010 year: 17(85%), None: 3(15%)
The type of purchased car:	Economy or City Car: 10(47%), Sedan: 3(14%), Family Car or Multi-Purpose Vehicle (MPV): 4(19%), Luxury or Sports Car :0, Sports Utility Vehicle (SUV): 2(10%), Pickup Truck: 0, I do not have a car : 2(10%)	Economy or City Car: 5(25%), Sedan: 3(15%), Family Car or Multi-Purpose Vehicle (MPV): 2(10%), Luxury or Sports Car: 0, Sports Utility Vehicle (SUV): 7(35%), Pickup Truck: 0, I do not have a car : 3(15%)
The type of used car:	Economy or City Car: 10(48%), Sedan: 2(10%), Family Car or Multi-Purpose Vehicle (MPV):3(14%), Luxury or Sports Car: 0, Sports Utility Vehicle (SUV):3(14%), Pickup Truck: 0, I do not use a car : 3(14%)	Economy or City Car: 5(25%), Sedan: 3(15%), Family Car or Multi-Purpose Vehicle (MPV): 1(5%), Luxury or Sports Car: 0, Sports Utility Vehicle (SUV): 6(30%), Pickup Truck: 0, I do not use a car: 5(25%)
Propulsion system of car bought:	Petrol: 9(43%), Diesel: 9(43%), LPG: 0, CNG: 0, BEV: 0, HEV: 1(5%), PHEV: 0, I do not have a car: 2(9%)	Petrol: 12(60%), Diesel: 4(20%), LPG: 0, CNG: 0, BEV: 1(5%), HEV: 0, PHEV: 0, I do not have a car: 3(15%)
Price range of car bought:	less than €10,000: 7(33%), between €10,000 and €20,000: 7(33%), between €20,001 and €30,000: 4(19%), between €30,001 and €40,000: 0, between €40,001 and €50,000: 1(5%), between €50,001 and €60,000: 0, between €60,001 and €70,000: 0, between €70,001 and €80,000: 0, between €80,001 and €90,000: 0, between €90,001 and €100,000: 0, more than €100,000: 0, I do not have a car: 2(10%)	less than ¥50,000: 3(15%), between ¥50,001 and ¥100,000: 2(10%), between ¥100,001 and ¥200,000: 5(25%), between ¥200,001 and ¥300,000: 5(25%), between ¥300,001 and ¥400,000: 2(10%), between ¥400,001 and ¥500,000: 0, between ¥500,001 and ¥600,000: 0, between ¥600,001 and ¥700,000: 0, between ¥700,001 and ¥800,000: 0, between ¥800,001 and ¥900,000: 0, more than ¥900,000: 0, I do not have a car: 3(15%)
Driving range with full tank (full charge):	less than 200 km: 0, between 201 and 300 km :1(5%), between 301 and 400 km: 5(24%), between 401 and 500 km: 2(9%), between 501 and 600 km: 1(5%), between 601 and 700 km: 3(14%), between 701 and 800 km: 1(5%), between 801 and 900 km: 2(9%), between 901 and 1,000 km: 3(14%),between 1,001 and 1,100 km: 1(5%), between 1,101 and 1,200 km: 0, more than 1,200 km: 0, I do not have a car :2(10%)	less than 200 km: 4(20%), between 201 and 300 km: 2(10%), between 301 and 400 km:0, between 401 and 500 km: 2(10%), between 501 and 600 km: 3(15%), between 601 and 700 km: 1(5%), between 701 and 800 km: 2(10%), between 801 and 900 km: 2(10%), between 901 and 1,000 km: 1(5%), between 1,001 and 1,100 km: 0, between 1,101 and 1,200 km: 0, more than 1,200 km: 1(5%), I do not have a car: 2(10%)
Possibility to buy EV:	Yes: 11(52%), No: 10(48%)	Yes: 12(60%), No: 8(40%)

Attitude description

The ranking of average values for each statement between Italy and China is shown in descending order in Table 37. We have specified some socioeconomic variables (s.g. gender, age, income, education level) with statements to compare the differences between these two countries based on their respective mean scores in order to distinguish the attitudes of respondents towards electric cars (Table 38 and Table 39).

The attitude with the highest mean score was “environmental friendly driving way”. It implies that both the Italian and Chinese respondents had a greater environmental awareness. The average value for Chinese respondents is slightly higher. The reason might be explained by the more serious environmental problems in China. Comparing performance to socioeconomic factors, we discovered that women in both nations have a substantially higher environmental sensitivity. The second important attitude is related to purchase price, which is shown by the statement “The purchase price is still too high. I prefer to wait”. Similar findings could be found in the reviewed literature, which were reported by Berkeley, Jarvis, and Jones (2018), Gnann et al. (2018), Danielis et al. (2018), Qian et al. (2019) and Giansoldati, Monte, et al. (2020). These findings have confirmed the need for additional improvements to reduce the purchasing price of EVs relative to traditional fuel vehicles. For Italian respondents, the middle-income class is more sensitive. Rural residents were more concerned about "high purchase price," particularly in the Italian sample, and those aged 40 to 60 are more sensitive to this factor. The third one is related to charging infrastructure. Both the Italian and Chinese respondents have shown high sensitivity to the statement “careful travel planning”. This is also consistent with the statements of “limited driving range” and “infrequent charging points”, and it reveals sensitive concerns of respondents who do not have a charging station or parking spots. This discovery is supported by She et al. (2017), Noel et al. (2020), Giansoldati, Monte, et al. (2020). Moreover, respondents in both Italy and China were concerned with “where to charge and at what cost”. In particular, Italian respondents who travel more than 50 km per day have shown great sensitivity to these concerns. This indicates that the statements may also have a more comprehensive performance than the other attitudes.

However, there is a significant difference between the statement “long charging time for electric cars”. It is ranked 5th out of 16 in China, while it is only 12th out of 16 in the Italian samples. The possible explanations might relate to the proportion of Italian respondents who have a garage or parking place for charging availability. This could also explain why Italian respondents are more sensitive to the “bureaucratically complicated and expensive process for building domestic charging”. The average value for “reduced maintenance costs” in the Chinese sample is significantly higher. In terms of socioeconomic characteristics, older-class and higher-income groups in Italy agreed more with the statement “lower maintenance cost”. This might be because of limited data collections in our pre-test sample.

Both the Italian and Chinese respondents were consistent with “low purchasing subsidies” and “low free parking hours”. In particular, those who live in large cities were more sensitive to these statements. This confirms the findings of insufficient incentives for the EV market. Respondents are not sensitive to the statements of “inferior driving”, “uncertainty of less pollution”, “safer driving electric cars”, and “safety regarding large battery size” in both Italy and China. This might benefit from the improvements in technology and probably indicates success in providing knowledge about electric cars.

The main differences between the Italian and Chinese pre-test sample are summarized as follows.

- The Chinese respondents are particularly sensitive to the statement of “long charging time for electric cars”.
- Older and higher-income groups in Italy were more sensitive to “reduced maintenance costs”.
- Men in Italy are more sensitive to “bureaucratically complicated and expensive processes for the construction of domestic charging”
- Chinese respondents are more sensitive to “restricted driving range”, particularly those who live in large cities and travel more than 100 km per day, whereas low-income Italians residing in small or medium-sized towns are more sensitive to this statement.

Table 37 Ranking of average values to the attitudes in Italy and China

	Italy		China
Attitudes	Mean Score	Attitudes	Mean Score
Driving an electric car is a more environmental friendly way of transportation than driving a conventional car.	4.12	Driving an electric car is a more environmental friendly way of transportation than driving a conventional car.	4.45
The purchase price is still too high. I prefer to wait.	4.08	Using an electric car requires careful travel planning.	4.15
Using an electric car requires careful travel planning.	4.08	Limited driving range would make/makes me feel uncomfortable to drive an electric car.	4
The electric car poses a problem of where to charge and at what cost, especially for those who do not own a garage.	3.76	The purchase price is still too high. I prefer to wait.	3.95
The construction of a domestic charging infrastructure is a bureaucratically complicated and expensive process, especially in an apartment.	3.72	Long time required for charging an electric car makes the use of electric cars unpractical.	3.9
It is not practical to drive an electric car because of the infrequent charging points.	3.58	The electric car poses a problem of where to charge and at what cost, especially for those who do not own a garage.	3.75
I would enjoy/enjoy driving an electric car more than driving a conventional car.	3.48	Electric cars have lower maintenance costs than conventional cars.	3.6
Limited driving range would make/makes me feel uncomfortable to drive an electric car.	3.48	The construction of a domestic charging infrastructure is a bureaucratically complicated and expensive process, especially in an apartment.	3.55
I think the number of free parking hours granted for electric cars enacted by some municipalities is too low.	3.4	I think that the purchasing subsidy for buying an electric car is currently too low.	3.55
I think that the purchasing subsidy for buying an electric car is currently too low.	3.32	I think the number of free parking hours granted for electric cars enacted by some municipalities is too low.	3.55
Electric cars have lower maintenance costs than conventional cars.	3.28	It is not practical to drive an electric car because of the infrequent charging point.	3.4
Long time required for charging an electric car makes the use of electric cars unpractical.	3.08	I would enjoy/enjoy driving an electric car more than driving a conventional car.	3.35
I think the performance of an electric car is inferior than the performance of a conventional car.	2.76	I would not feel safe driving an electric car given the large size of the battery and considering the risk of fire.	3.3
I think electric cars are safer to drive than conventional cars.	2.72	I think the performance of an electric car is inferior than the performance of a conventional car.	3.2
I am not convinced that electric cars pollute less than conventional cars due to battery disposal.	2.64	I think electric cars are safer to drive than conventional cars.	3.1
I would not feel safe driving an electric car given the large size of the battery and considering the risk of fire.	2.4	I am not convinced that electric cars pollute less than conventional cars due to battery disposal.	3

Table 38 Average values of statements with socio-economic characteristic in Italy

	Gender		Age			Education level						Employment						City Size			
Statements	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A11	A12	A13	A14	A15	A16	A17	A18	A19	A20	Total
The purchase price is still too high. I prefer to wait.	4.2	4.0	3.8	4.7	3.7	3.5	5.0	4.0	4.2	4.0	5.0	5.0	4.7	4.5	5.0	3.7	2.7	2.5	4.2	4.7	4.1
Electric cars have lower maintenance costs than conventional cars.	3.3	3.3	2.8	3.6	4.7	3.0	4.0	3.2	3.0	3.5	3.0	3.0	3.9	3.5	4.0	2.7	3.0	2.5	3.3	3.8	3.3
The construction of a domestic charging infrastructure is a bureaucratically complicated and expensive process, especially in an apartment.	3.2	4.1	3.5	4.0	4.0	3.5	5.0	3.8	3.6	3.6	4.0	4.0	3.4	4.5	5.0	3.4	4.3	4.5	3.2	3.8	3.7
The electric car poses a problem of where to charge and at what cost, especially for those who do not own a garage.	3.9	3.7	3.5	3.9	4.3	2.5	4.0	3.7	3.8	4.0	4.0	4.0	4.1	4.0	4.0	3.3	3.7	4.0	3.9	4.0	3.8
Driving an electric car is a more environmental friendly way of transportation than driving a conventional car.	4.5	3.9	4.4	3.6	4.7	4.5	5.0	4.0	3.8	4.2	4.0	4.0	4.1	3.5	5.0	4.2	4.0	4.5	4.5	4.0	4.1
I am not convinced that electric cars pollute less than conventional cars due to battery disposal.	2.4	2.8	2.3	3.4	1.7	2.0	1.0	3.3	2.6	2.5	3.0	3.0	2.9	3.0	1.0	2.4	2.7	1.5	2.4	3.0	2.6
It is not practical to drive an electric car because of the infrequent charging points.	3.5	3.6	3.7	3.9	2.3	3.0	3.0	3.7	4.2	3.4	3.0	3.0	3.3	4.5	3.0	3.9	3.3	4.5	3.5	3.5	3.6
Long time required for charging an electric car makes the use of electric cars unpractical.	3.1	3.1	3.1	3.3	2.3	2.5	4.0	3.0	3.0	3.2	3.0	3.0	3.2	3.5	4.0	2.9	2.7	2.5	3.1	3.5	3.1
Using an electric car requires careful travel planning.	4.0	4.1	4.1	4.1	4.0	4.5	5.0	3.8	4.2	4.1	3.0	3.0	4.1	5.0	5.0	4.1	3.3	3.0	4.0	4.3	4.1
I think the performance of an electric car is inferior than the performance of a conventional car.	2.9	2.7	2.6	3.0	2.7	1.5	4.0	3.3	2.4	2.7	3.0	3.0	2.8	3.0	4.0	2.6	2.7	2.0	2.9	3.3	2.8
I think electric cars are safer to drive than conventional cars.	2.3	3.0	2.5	2.9	3.0	3.0	3.0	2.3	3.2	2.6	3.0	3.0	2.9	3.0	3.0	2.6	2.3	3.0	2.3	2.3	2.7
I would not feel safe driving an electric car given the large size of the battery and considering the risk of fire.	2.5	2.3	2.3	2.4	2.7	1.0	2.0	2.3	2.8	2.5	3.0	3.0	2.3	3.5	2.0	2.1	2.7	3.0	2.5	2.5	2.4
I think that the purchasing subsidy for buying an electric car is currently too low.	3.4	3.3	3.5	3.0	3.3	2.5	4.0	3.7	3.8	2.9	4.0	4.0	3.1	3.0	4.0	3.6	3.0	4.5	3.4	3.3	3.3
I think the number of free parking hours granted for electric cars enacted by some municipalities is too low.	3.3	3.5	3.5	3.2	3.7	3.5	3.0	3.3	3.8	3.3	3.0	3.0	3.1	4.0	3.0	3.4	4.0	4.5	3.3	2.8	3.4
I would enjoy/enjoy driving an electric car more than driving a conventional car.	3.7	3.3	3.5	3.0	4.7	3.5	4.0	3.0	4.0	3.4	4.0	4.0	3.4	3.5	4.0	3.3	3.7	4.0	3.7	3.5	3.5
Limited driving range would make/makes me feel uncomfortable to drive an electric car.	3.7	3.3	3.5	4.2	1.0	3.5	1.0	3.8	3.0	3.7	4.0	4.0	3.9	4.0	1.0	3.3	3.0	2.5	3.7	3.5	3.5

Legend - A1: Female; A2: Male; A3: Young; A4: Middle; A5: Old; A6: High school diploma A7: Junior high school; A8: Bachelor; A9: Master; A10: Post graduate; A11: Professional degree; A12: Entrepreneur; A13: Executive employee; A14: Retired; A15: Other; A16: Student; A17: White collar; A18: Large city; A19: Small or medium town; A20: Rural area

	House type				Income level			Driving distance				Avialibility for chagring station			Total
Statements	B1	B2	B3	B4	B5	B6	B7	B8	B9	B10	B11	B12	B13	B14	
Average of The purchase price is still too high. I prefer to wait.	4.1	3.3	4.5	5.0	4.3	4.0	3.0	3.9	4.5	5.0	3.8	4.0	3.8	4.3	4.1
Average of Electric cars have lower maintenance costs than conventional cars.	3.4	3.3	3.1	3.0	2.9	3.6	5.0	3.3	2.3	3.7	3.5	3.2	3.0	3.6	3.3
Average of The construction of a domestic charging infrastructure is a bureaucratically complicated and expensive process, especially in an apartment.	3.9	3.5	3.9	2.0	4.1	3.0	3.5	3.7	3.5	3.7	3.8	3.7	3.5	3.9	3.7
Average of The electric car poses a problem of where to charge and at what cost, especially for those who do not own a garage.	3.9	3.7	3.6	4.0	3.7	3.7	4.5	3.9	3.0	4.0	3.9	3.6	3.7	4.0	3.8
Average of Driving an electric car is a more environmental friendly way of transportation than driving a conventional car.	4.1	4.3	3.9	5.0	3.9	4.6	4.5	4.4	3.8	3.7	4.2	3.9	4.3	4.2	4.1
Average of I am not convinced that electric cars pollute less than conventional cars due to battery disposal.	3.1	1.8	2.8	2.0	2.9	2.1	2.0	2.4	3.3	3.3	2.4	2.9	2.3	2.6	2.6
Average of It is not practical to drive an electric car because of the infrequent charging points.	3.8	3.3	3.5	4.0	3.9	3.4	2.0	4.0	3.3	4.0	3.3	3.7	4.0	3.2	3.6
Average of Long time required for charging an electric car makes the use of electric cars unpractical.	3.5	2.3	3.0	4.0	3.3	3.0	1.5	3.1	3.3	3.3	2.9	3.0	3.2	3.1	3.1
Average of Using an electric car requires careful travel planning.	3.9	3.8	4.4	5.0	4.2	4.0	3.5	4.3	4.0	4.3	3.9	3.9	4.2	4.2	4.1
Average of I think the performance of an electric car is inferior than the performance of a conventional car.	3.1	2.7	2.5	2.0	2.9	2.6	2.0	3.3	3.0	3.3	2.2	2.9	3.0	2.4	2.8
Average of I think electric cars are safer to drive than conventional cars.	2.6	2.8	2.8	3.0	2.8	2.6	3.0	2.4	2.5	1.7	3.3	2.8	2.7	2.7	2.7
Average of I would not feel safe driving an electric car given the large size of the battery and considering the risk of fire.	2.4	2.5	2.4	2.0	2.5	2.0	3.0	2.9	2.3	2.0	2.3	2.3	2.8	2.2	2.4
Average of I think that the purchasing subsidy for buying an electric car is currently too low.	3.2	3.5	3.1	5.0	3.4	3.3	3.0	3.4	3.3	3.0	3.4	3.3	3.8	3.0	3.3
Average of I think the number of free parking hours granted for electric cars enacted by some municipalities is too low.	3.2	4.2	3.1	3.0	3.6	2.9	4.0	3.0	3.5	3.0	3.7	3.3	3.3	3.6	3.4
Average of I would enjoy/enjoy driving an electric car more than driving a conventional car.	3.4	3.5	3.4	5.0	3.3	3.4	5.0	3.1	3.8	2.7	3.8	3.6	3.2	3.6	3.5
Average of Limited driving range would make/makes me feel uncomfortable to drive an electric car.	4.1	3.2	3.0	3.0	3.6	3.9	1.0	3.1	4.0	4.7	3.2	3.3	3.8	3.4	3.5

Legend - B1: Apartment with garage or private parking space; B2: Apartment without garage or private parking space; B3: Detached house with a garage or private parking space; B4: Detached house without a garage or private parking space; B5: middle; B6: poor; B7: rich; B8: ≤ 20 km; B9: 20~50 km; B10: 50~80 km; B11: I don’t regularly drive a car; B12: I do not know; B13: No; B14: Yes

Table 39 Average values of statements with socio-economic characteristic in China

	Gender		Education level			Employment			City Size					Tot
Statements	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	
The purchase price is still too high. I prefer to wait.	3.9	4.0	3.7	4.3	4.0	3.8	4.3	3.9	4.0	3.7	5.0	3.6	4.3	4.0
Electric cars have lower maintenance costs than conventional cars.	3.5	3.8	3.1	4.0	4.0	3.4	3.5	3.7	3.0	3.0	5.0	3.9	3.5	3.6
It is not practical to drive an electric car because of the infrequent charging point.	3.5	3.2	3.3	3.4	3.7	3.8	3.5	3.2	4.0	2.7	5.0	3.0	3.8	3.4
The construction of a domestic charging infrastructure is a bureaucratically complicated and expensive process, especially in an apartment.	3.5	3.6	3.2	3.6	4.3	3.6	4.0	3.4	3.0	3.3	5.0	3.0	4.0	3.6
The electric car poses a problem of where to charge and at what cost, especially for those who do not own a garage.	4.0	3.4	3.8	3.8	3.7	4.0	4.0	3.5	4.0	3.7	5.0	3.3	4.0	3.8
Driving an electric car is a more environmental friendly way of transportation than driving a conventional car.	4.6	4.2	4.7	4.1	4.7	4.8	5.0	4.1	5.0	4.0	5.0	4.6	4.4	4.5
I am not convinced that electric cars pollute less than conventional cars due to battery disposal.	2.9	3.1	2.7	3.0	4.0	3.0	3.5	2.8	3.0	1.7	5.0	2.9	3.4	3.0
Long time required for charging an electric car makes the use of electric cars unpractical.	3.8	4.0	3.6	4.0	4.7	3.8	4.0	3.9	4.0	3.0	5.0	3.7	4.3	3.9
Using an electric car requires careful travel planning.	4.2	4.1	4.0	4.3	4.3	4.8	4.3	3.8	4.0	3.0	5.0	4.3	4.4	4.2
I think the performance of an electric car is inferior than the performance of a conventional car.	3.5	2.9	3.3	3.0	3.3	3.8	3.5	2.8	3.0	2.7	5.0	2.9	3.5	3.2
I think electric cars are safer to drive than conventional cars.	3.1	3.1	3.2	3.0	3.0	3.2	3.5	2.9	3.0	2.7	5.0	2.9	3.3	3.1
I would not feel safe driving an electric car given the large size of the battery and considering the risk of fire.	3.1	3.6	3.1	3.3	4.0	3.2	3.5	3.3	3.0	3.0	5.0	2.7	3.8	3.3
I think that the purchasing subsidy for buying an electric car is currently too low.	3.5	3.7	3.4	3.4	4.3	3.4	4.0	3.5	2.0	2.7	5.0	3.3	4.1	3.6
I think the number of free parking hours granted for electric cars enacted by some municipalities is too low.	3.6	3.4	3.2	3.5	4.7	3.2	4.0	3.5	2.0	2.3	5.0	3.6	4.0	3.6
I would enjoy/enjoy driving an electric car more than driving a conventional car.	3.5	3.2	3.1	3.3	4.3	3.4	3.8	3.2	3.0	3.0	5.0	3.1	3.5	3.4
Limited driving range would make/makes me feel uncomfortable to drive an electric car.	4.1	3.9	3.7	4.4	4.0	4.0	4.5	3.8	4.0	3.7	5.0	3.9	4.1	4.0

Legend - C1: Female; C2: Male; C3: Bachelor; C4: Master; C5: Post Graduate; C6: Executive employee; C7: Other; C8: White collar; C9: Small cities; C10: Medium cities; C11: Large cities; C12: Super cities; C13: Very large cities

	House type				Income level		Avialibility for garage		Driving distance						Avialibility for chagring station			Tot
Statements	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D11	D12	D13	D14	D15	D16	D17	
The purchase price is still too high. I prefer to wait.	3.9	5.0	3.9	4.0	3.0	4.0	3.9	4.0	4.1	4.0	4.0	3.0	5.0	3.5	4.1	3.0	3.9	4.0
Electric cars have lower maintenance costs than conventional cars.	3.8	5.0	3.3	3.0	5.0	3.5	3.7	3.4	3.8	3.6	3.0	4.0	4.0	3.3	4.1	2.0	3.3	3.6
It is not practical to drive an electric car because of the infrequent charging point.	3.6	5.0	3.1	2.0	3.0	3.4	3.3	3.6	4.0	2.8	4.0	1.0	5.0	3.0	4.1	3.0	2.8	3.4
The construction of a domestic charging infrastructure is a bureaucratically complicated and expensive process, especially in an apartment.	3.9	5.0	3.0	3.0	3.0	3.6	3.5	3.6	3.8	3.4	3.0	2.0	4.0	3.8	4.1	3.0	3.1	3.6
The electric car poses a problem of where to charge and at what cost, especially for those who do not own a garage.	3.8	5.0	3.5	4.0	2.0	3.8	3.7	3.8	3.9	3.6	4.0	4.0	5.0	3.3	4.1	3.0	3.5	3.8
Driving an electric car is a more environmental friendly way of transportation than driving a conventional car.	4.7	5.0	4.4	2.0	4.0	4.5	4.5	4.3	4.5	4.0	5.0	5.0	4.0	4.8	4.7	3.0	4.4	4.5
I am not convinced that electric cars pollute less than conventional cars due to battery disposal.	3.1	5.0	2.9	1.0	5.0	2.9	2.8	3.2	3.8	2.2	4.0	1.0	3.0	2.8	3.2	3.0	2.8	3.0
Long time required for charging an electric car makes the use of electric cars unpractical.	3.9	5.0	3.9	3.0	4.0	3.9	3.6	4.2	4.3	3.6	4.0	3.0	4.0	3.8	4.0	3.0	3.9	3.9
Using an electric car requires careful travel planning.	4.3	5.0	4.1	2.0	4.0	4.2	4.2	4.1	4.3	4.2	5.0	3.0	5.0	3.8	4.3	3.0	4.1	4.2
I think the performance of an electric car is inferior than the performance of a conventional car.	3.2	5.0	3.1	2.0	1.0	3.3	2.9	3.6	3.3	3.4	5.0	2.0	3.0	2.8	3.4	3.0	3.0	3.2
I think electric cars are safer to drive than conventional cars.	3.3	5.0	2.8	2.0	5.0	3.0	3.2	3.0	4.0	2.0	4.0	3.0	3.0	2.5	3.8	2.0	2.6	3.1
I would not feel safe driving an electric car given the large size of the battery and considering the risk of fire.	3.2	5.0	3.3	3.0	1.0	3.4	3.2	3.4	3.6	3.4	3.0	2.0	2.0	3.3	3.2	4.0	3.3	3.3
I think that the purchasing subsidy for buying an electric car is currently too low.	3.5	5.0	3.6	2.0	3.0	3.6	3.5	3.6	3.9	3.2	4.0	4.0	2.0	3.5	3.7	3.0	3.5	3.6
I think the number of free parking hours granted for electric cars enacted by some municipalities is too low.	3.5	5.0	3.8	1.0	3.0	3.6	3.5	3.6	3.8	2.8	4.0	3.0	5.0	3.8	4.0	3.0	3.2	3.6
I would enjoy/enjoy driving an electric car more than driving a conventional car.	3.3	5.0	3.1	4.0	4.0	3.3	3.2	3.6	3.6	2.8	4.0	3.0	4.0	3.3	3.7	3.0	3.1	3.4
Limited driving range would make/makes me feel uncomfortable to drive an electric car.	4.2	5.0	3.8	3.0	4.0	4.0	4.1	3.9	4.0	4.0	4.0	4.0	5.0	3.8	4.1	3.0	4.0	4.0

Legend - D1: Apartment with garage or private parking space; D2: Detached house with a garage or private parking space; D3: Apartment without garage or private parking space; D4: Detached house without a garage or private parking space; D5: Middle; D6: Rich; D7: No; D8: Yes; D9: ≤20 km; D10: 20-50km; D11: 50~80 km; D12: 80~100 km; D13: ≥ 100 km; D14: I don't regularly drive a Dar; D15: I do not know ; D16: No; D17:Yes

Econometric results

In order to distinguish the differences in EVs choices between Italian and Chinese respondents, we examined them by using the Apollo package developed in R. The steps we have used in Apollo are listed in Figure 11. The estimation results of the MNL model between Italy and China are presented in Table 40.

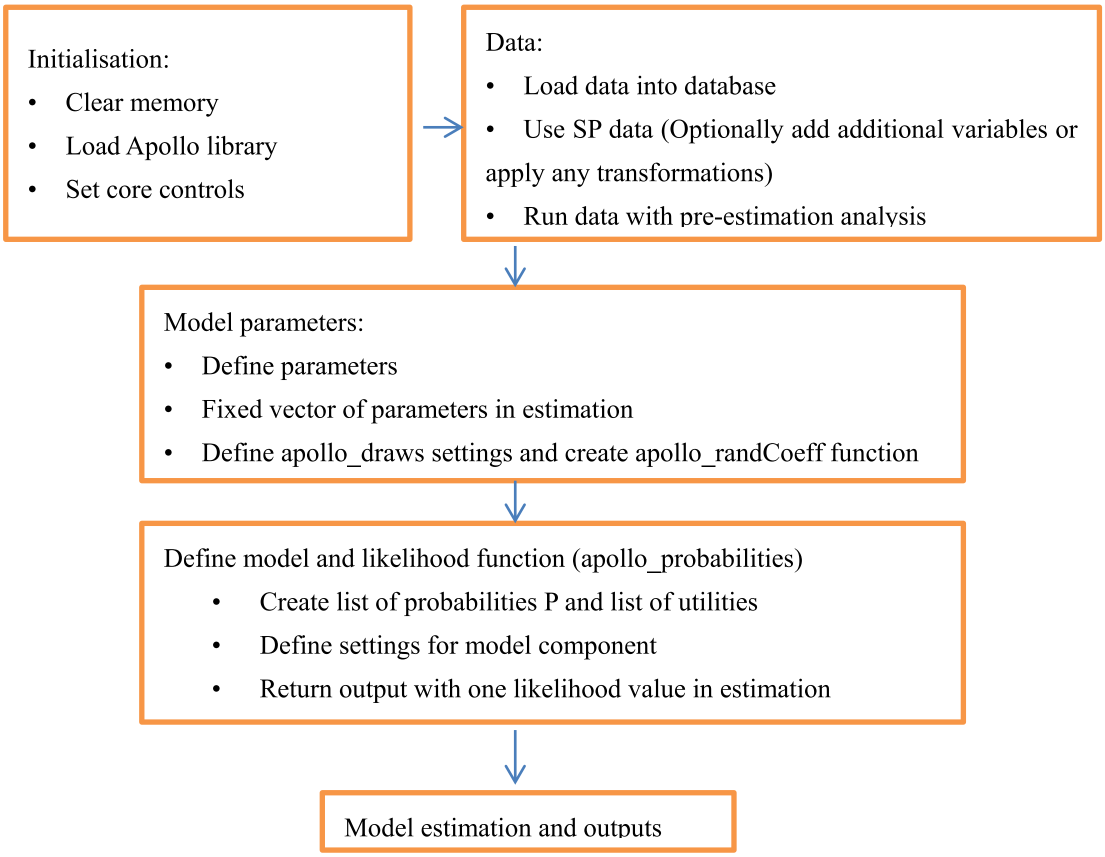


Figure 11 General structures of Apollo

In general, the adjust Rho_square value indicates that the overall model fitness in Italy and China is good. We have used petrol cars as the reference alternative, assumed all parameters to be normally distributed, and used the log-likelihood (LL) function at convergence to assess the model fit goodness. The coefficient of ASC_BEV in both Italy and China are positive and statistically significant, implying that respondents have high utility on BEVs. The coefficients of purchase price are negative in both Italy and China, indicating a higher price would reduce the utility of BEVs. The coefficient of the driving range of BEVs is not significant, indicating driving range would not be a cause for the utility of BEVs, but this might be because of the limited data in our pre-test sample; we will check this range attribute in the next survey.

To further distinguish the heterogeneity preference on socio-economic characteristics of BEVs and ICEVs, we have selected some socio-economic variables including age, gender, household income, garage availability and city size and interacted them with the ASC_BEV to analyze the utilities of respondents in these two countries. In Italy, men have a greater utility for selecting BEVs than women. the interaction term of gender on purchase price and driving range reveals that the coefficients of males on purchase price are statistically significantly positive, showing that men in Italy are more price sensitive than women. The people who live in large cities show a high utility on BEVs in Italy.

Table 40 Estimation results with socio-economic characteristic in Italy and China

Variables	Italy		China	
	Coefficient	t.rat.0)	Coefficient	t.rat.(0)
asc_petrol	0	NA	0	NA
asc_diesel	0.378	1.650	-1.585***	-6.559
asc_lpg	-0.499*	-1.920	/	/
asc_cng	-1.418*	-1.930	/	/
asc_bev	3.318*	1.750	2.355***	2.342
asc_hev	1.209***	5.020	-0.687***	-3.675
asc_phev	0.630	1.470	-0.444**	-2.142
b_price	-0.264***	-12.640	-0.011***	-5.636
b_range_ice	0.003***	7.550	0.002***	5.248
b_range_bev	-0.001	-0.120	-0.003	-1.417
b_male	1.451*	1.59	0.474	0.285
b_price_male	0.074**	2.010	0.001	0.279
b_largecity	3.629**	1.921	/	/

Note: ***p < 0.01, **p < 0.05, *p < 0.1

2 Conclusions of pre-test

In this chapter, we have conducted a pre-test survey by estimating a multinomial logit (MNL) model to compare differences in customer preference for electric cars between Italy and China. Specifically, we have identified the stated preferences concerning BEVs, taking into account purchase price and driving range, together with some socio-economic characteristics in these two countries. The results demonstrated that our survey was well-designed.

Compared with the other vehicles (petrol, diesel, LPG, CNG, HEV, PHEV), *ceteris paribus*, respondents have a higher utility on BEVs in both two countries. The analysis of the stated preference choices performed with the multinomial logit model confirmed that the (net) purchase price is the most relevant vehicle attribute in both two countries. Purchase price plays significant role on BEVs. The driving range of BEVs in our pre-test is not significant, but as the data in our pre-test is limited, we will research it in the next experiment. Considering socio-economic characteristics, men and people who lived in large cities in Italy has high utility on BEVs.

The statement concerning the “limited driving range” is significant for both countries. In addition, both Italian and Chinese respondents are sensitive to “careful travelling plan” and “infrequent charging points”. People who do not have a charging or parking place are more sensitive to the statement of “Where to charge and at what cost”. It is worth noting that the attitude toward “environmental friendly driving way” is significant in both Italy and China, especially for the Chinese sample. This could be explained the serious environment pollution problem in China. There is a remarkable difference on the statement of “long charging time”. The Chinese respondents paid more attention to this aspect than the Italians. The possible explanation might be associated with the fact that a smaller proportion of Chinese respondents (55%) than Italian respondents (71%) owned a garage or charging parking space. The ones who have a garage would rely on home charging and be less sensitive to the charging time. This also explains why Italians are more sensitive to “bureaucratically complicated and expensive process for the construction of domestic charging”.

As mentioned above, the results of our pre-test survey has confirmed our design is appropriate. We will conduct our survey in the next stages based on the pre-test questionnaires.

Appendix D : Factor Analysis in R

1 Exploratory factor analysis (EFA)

```
### Set the working directory
Setwd ("C:/ EFA_IT_25_12_2021")
### Import the file and describe the data
master = read.csv("04_12_2021_Scale Data for R_IT.csv")
describe (master)
### Find the reverse questions and to recode them, to make sure they are positive if they scored lower on that question
Table (master$Q1)
master [ , c(1,3,4,5,7,8,9,10,12,13,14,16)] = 6 - master[ , c(1,3,4,5,7,8,9,10,12,13,14,16)]
table (master$Q1)
### Check data accuracy, find whether excist the missing data or not
percentmissing = function (x) {
sum (is.na (x)) / length (x) * 100
}
missing = apply (master, 1, percentmissing)
table (missing)
### If there is some missing data, exclude the participant missing too much data
replacepeople = subset (master, missing <= 5)
### Make sure the columns aren't missing too much
Apply (replacepeople, 2, percentmissing)
### Replace away the missing data, use the package ("mice")
install.packages("mice")
library(mice)
tempnomiss = mice(replacepeople)
nomiss = complete(tempnomiss, 1)
summary(nomiss)
### Outliers: check for weird patterns of scores, use Mahalanobis to figure out if someone's pattern of data is strange to eliminate them
cutoff = qchisq(1-.001, ncol(nomiss))
mahal = mahalanobis(nomiss,
                    colMeans(nomiss),
                    cov(nomiss))
### Get the χ2 and df
cutoff
ncol(nomiss)
summary(mahal < cutoff)
```

```
### Find false data and exclude them from outliers
nonew = subset(nomiss, mahal < cutoff)

### Additivity: check for questions to be correlated, use the rule of r < .999
correl = cor(nonew, use = "pairwise.complete.obs")
symnum(correl)
correl
### Assumption set up, use the fake regression in order to screen EFA with a regular regression analysis
random = rchisq(nrow(nonew), 5)
fake = lm(random~., data = nonew)
standardized = rstudent(fake)
fitted = scale(fake$fitted.values)
### Normality
hist(standardized)
### Linearity
qqnorm(standardized)
abline(0,1)
### Homogeneity
plot(fitted,standardized)
abline(0,0)
abline(v = 0)
### Running the EFA analysis
library(psych)
library(GPArotation)
### Check the correlation adequacy by using Bartlett's test (chi-square), p < .001 is large enough correlation for EFA, Check the sampling adequacy to use KMO, the value closed to one is better
cortest.bartlett(correl, n = nrow(nonew))
KMO(correl)
###     Factors extraction, by using the rules oftheory, Parallel analysis, Kaiser criterion
nofactors = fa.parallel(nonew, fm="ml", fa="fa")
sum(nofactors$fa.values > 1.0) ##old kaiser criterion
sum(nofactors$fa.values > .7) ##new kaiser criterion
### Analyse the structure, try to find a simple structure with a four factor model, use the rotation method of Oblimin and the math type of maximum likelihood, check how much variance each factor accounted for and the correlations of these four factors
round1 = fa(nonew, nfactors=4, rotate = "oblimin", fm = "ml")
round1
```

```r
round2 = fa(nonew[ , -c(1,2,10,11,12,15)], nfactors=4, rotate = "oblimin", fm ="ml")
round2
### Get the model fit indices of CFI to check goodness
finalmodel = fa(nonew[ , -c(1,2,10,11,12,15)], nfactors=4, rotate = "oblimin", fm = "ml")
1 - ((finalmodel$STATISTIC-finalmodel$dof)/
        (finalmodel$null.chisq-finalmodel$null.dof))
### Use Cronbach's alpha to check reliability, normally the value is between 0.5-0.8 can be considered as good
factor1 = c(8,9,16)
factor2 = c(6,7)
factor3 = c(3,4,5)
factor4 = c(13,14)
psych::alpha(nonew[ , factor1])
psych::alpha(nonew[ , factor2])
psych::alpha(nonew[ , factor3])
psych::alpha(nonew[ , factor4])
### Create new factor scores
nonew$f1 = apply(nonew[ , factor1], 1, mean) ##creates average scores
nonew$f2 = apply(nonew[ , factor2], 1, mean) ##creates average scores
nonew$f3 = apply(nonew[ , factor3], 1, mean) ##creates average scores
nonew$f4 = apply(nonew[ , factor4], 1, mean) ##creates average scores
### Get standard deviation to check data reasonable or not in the new four factor model
sd(nonew$f1)
sd(nonew$f2)
sd(nonew$f3)
sd(nonew$f4)
```

2 Confirmatory factor analysis (CFA)

```
### Set the working directory
setwd("C:/ EFA_IT_25_12_2021")
### Import the file and describe the data
master = read.csv("04_12_2021_Scale Data for R_IT.csv")
describe(master)
### Find the reverse questions and to recode them, to make sure they are positive if they scored lower on that question
table(master$Q1)
master[ , c(1,3,4,5,7,8,9,10,12,13,14,16)] = 6 - master[ , c(1,3,4,5,7,8,9,10,12,13,14,16)]
table(master$Q1)
### Check data accuracy, find whether excist the missing data or not
percentmissing = function (x){
sum (is.na(x)) / length(x) * 100
}
missing = apply(master, 1, percentmissing)
table(missing)
### If there is some missing data, exclude the participant missing too much data
replacepeople = subset(master, missing <= 5)
### Make sure the columns aren't missing too much
apply(replacepeople, 2, percentmissing)
### Replace away the missing data, use the package ("mice")
install.packages("mice")
library(mice)
tempnomiss = mice(replacepeople)
nomiss = complete(tempnomiss, 1)
summary(nomiss)
### Outliers: check for weird patterns of scores, use Mahalanobis to figure out if someone's pattern of data is strange to eliminate them
cutoff = qchisq(1-.001, ncol(nomiss))
mahal = mahalanobis(nomiss,
                    colMeans(nomiss),
                    cov(nomiss))
### Get the χ2 and df to check outliers
cutoff
ncol(nomiss)
summary(mahal < cutoff)
### Find false data and exclude them from outliers
nonew = subset(nomiss, mahal < cutoff)
### Additivity: check for questions to be correlated, use the rule of r < .999
```

```
correl = cor(nonew, use = "pairwise.complete.obs")
symnum(correl)
correl
### Assumption set up, use the fake regression in order to screen EFA with a regular regression analysis
random = rchisq(nrow(nonew), 5)
fake = lm(random~., data = nonew)
standardized = rstudent(fake)
fitted = scale(fake$fitted.values)
### Normality
hist(standardized)
### Linearity
qqnorm(standardized)
abline(0,1)
### Homogeneity
plot(fitted,standardized)
abline(0,0)
abline(v = 0)
### Create the models, firstly check the model include all of 16 questions, then run the model to check model fit and use modindices functio to exculde the equality factor that worked on model
Old.model = '
chargingrange     =~ Q3 + Q4 + Q5 + Q8 + Q9 + Q16
economic          =~ Q1 + Q2 + Q13 + Q14
enviornment       =~ Q6 + Q7
driving           =~ Q10 + Q11 + Q12 + Q15
'
four.model = '
chargingrange     =~ Q3   + Q8 + Q9 + Q16 # + Q5# + Q4
economic          =~ Q1   + Q13 # + Q14   # + Q2
enviornment       =~ Q6 + Q7
driving           =~ Q10   + Q12   + Q15 #+ Q11
'
### Run the models
four.fit = cfa(four.model, data = noout)
### Create path diagram of model
semPaths(four.fit, whatLabels="std", layout="tree",edge.color = "blue",edge.label.cex = 1)
### Summaries model fit by using the model indices of RMSEA, SRMR , TLI and CFI
summary(four.fit, standardized=TRUE, rsquare=TRUE)
modindices(four.fit, sort. = TRUE, minimum.value = 30.00)
```

```
fitMeasures(four.fit)

### Check the reliability of four factors
factor1 = c(3,8,9,16)
factor2 = c(6,7)
factor3 = c(1,13)
factor4 = c(10,12,15)
psych::alpha(noout[ , factor1])
psych::alpha(noout[ , factor2])
psych::alpha(noout[ , factor3])
psych::alpha(noout[ , factor4])
```

Appendix E: Agent-based Model Process

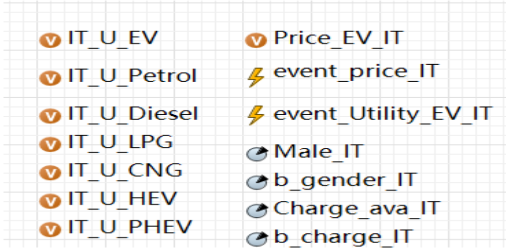


Figure 12Variables, Parameters and Behaviors in our ABM example (Part)

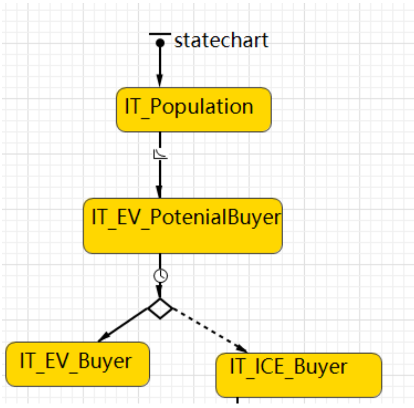
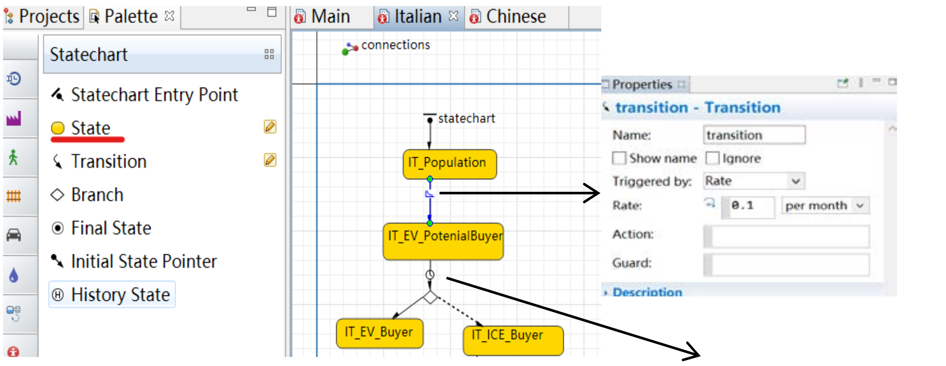


Figure 13 The main statechart in ABM (Part)



Timeout: change state if the other awaited events do not occur within the specified time interval, in our sample, we set timeout as 1 per month.

Figure 14 Created Statechart and Transition

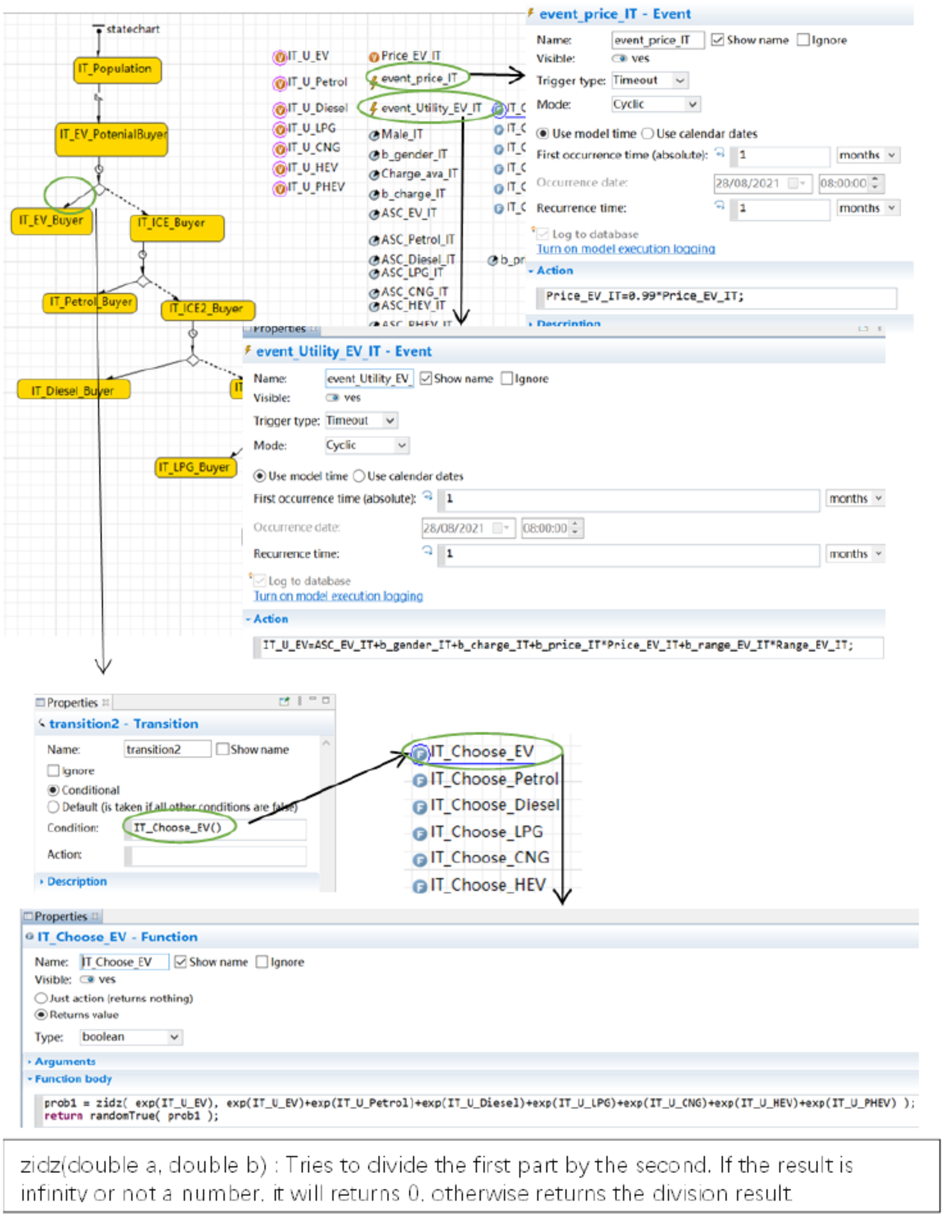


Figure 15 Events, Branch and Function created

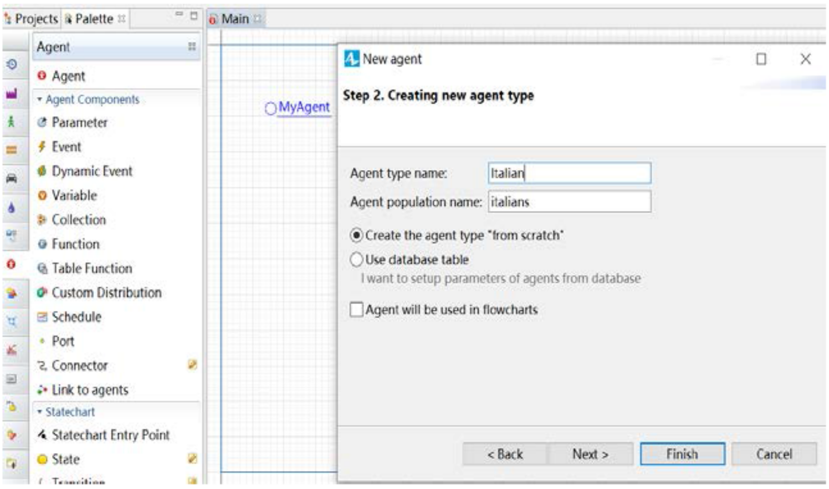


Figure 16 Created Models and Agents in Anylogic

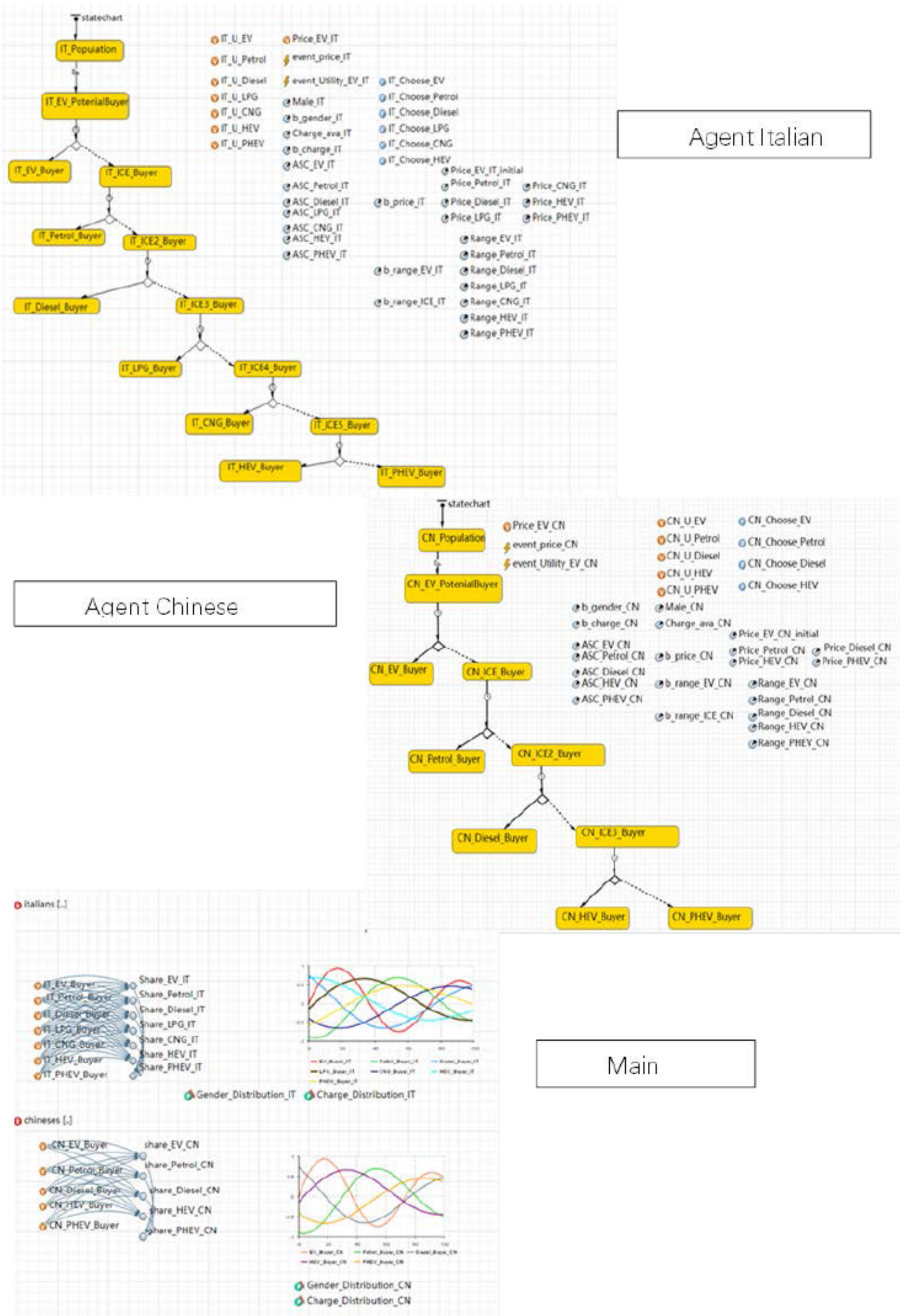


Figure 17 The Agent-Based Model for Italy and China

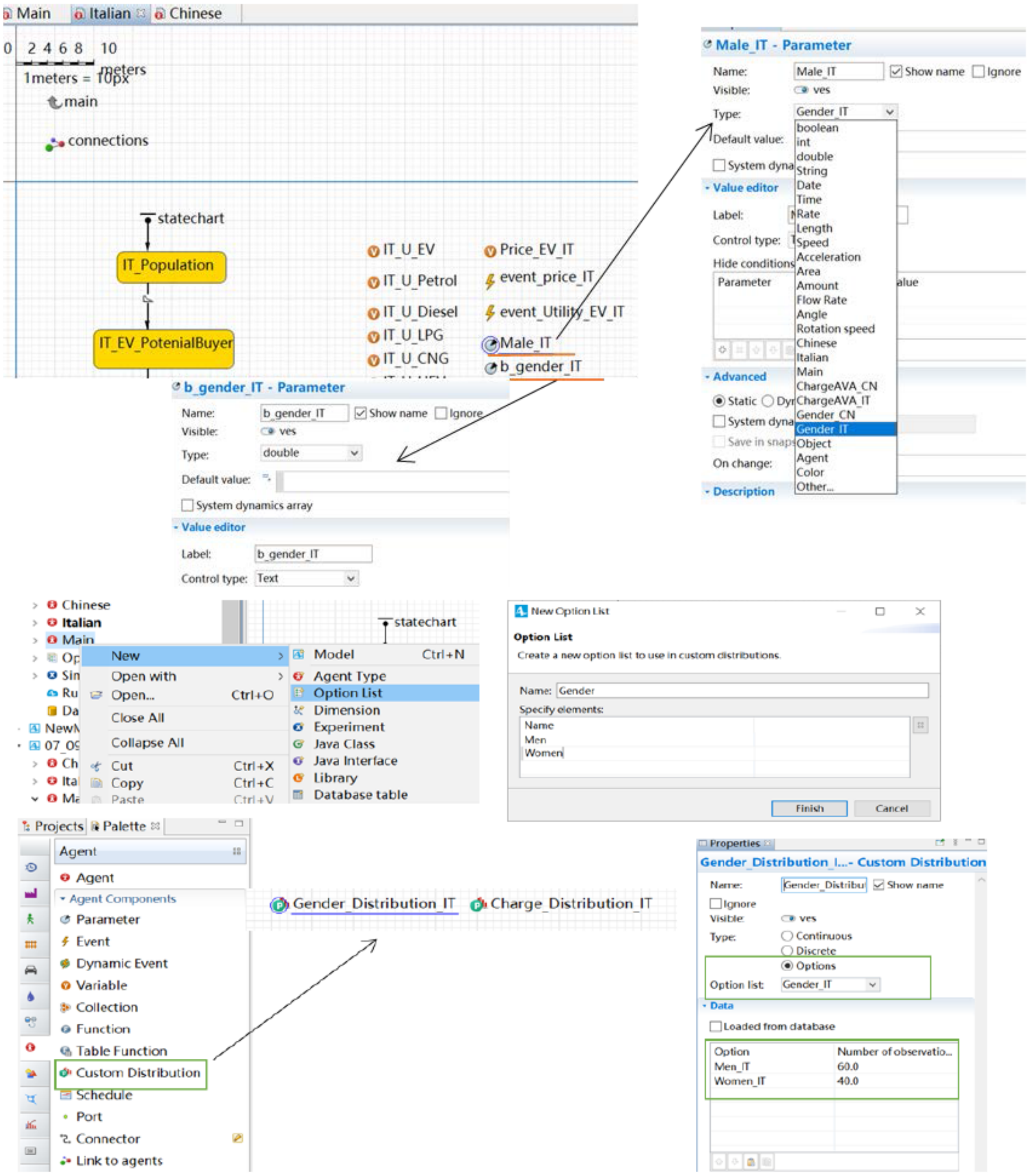


Figure 18 Option list created

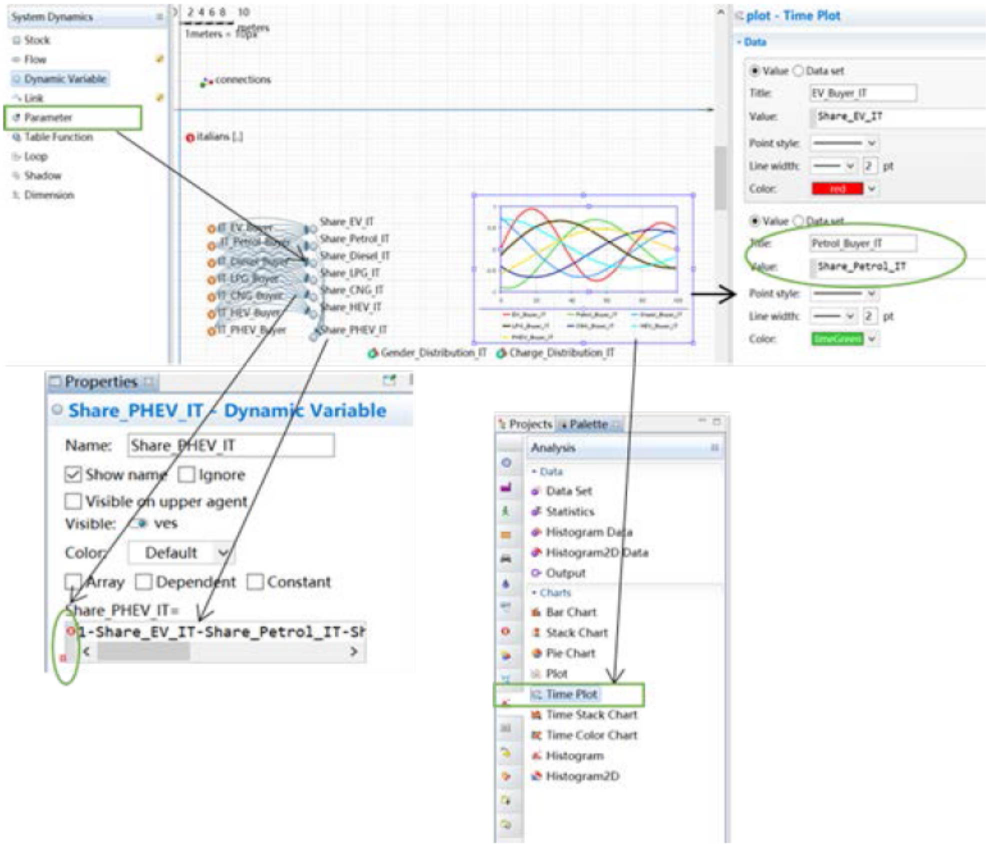


Figure 19 Time Plot and Dynamic Variable