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Determining the Factors That Influence Electric Vehicle Adoption: A Stated Preference Survey Study in Beijing, China

Ziwen Ling [1], Christopher R. Cherry [2,*] and Yi Wen [2]

[1] Virginia Department of Transportation, Richmond, VA 23219, USA; zling@vols.utk.edu
[2] Department of Civil and Environmental Engineering, University of Tennessee, Knoxville, TN 37996, USA; ywen4@vols.utk.edu
* Correspondence: cherry@utk.edu; Tel.: +1-(865)-974-7710

Abstract: The transition from conventional vehicles (CVs) to electric vehicles (EVs) could be promising in tackling environmental challenges in China. Using a sample of 1216 respondents in Beijing, China, our study intends to understand the underlying factors that drive the decision to purchase an EV among potential Chinese vehicle purchasers. We built two choice models to estimate vehicle purchase behavior and fuel choice. We found that males and having higher household income are associated with greater intention to purchase EVs (both plug-in and battery electric vehicles). However, a previous inclination to choose CV negatively impacted willingness to buy EVs. Between specific EV types, we found that Plug-in Hybrid EV (PHEV) purchase was negatively associated with plans to obtain a driver's license within three years and longer durations of having owned a motorized vehicle first. Yet, the number of electric bicycles in the household was positively associated with PHEV-purchase likelihood. For Battery EVs (BEV), we found that respondents who had previous experience with an EV (either as a driver or passenger) were more likely to purchase a BEV while existing ownership of a driver's license and a higher purchase budget reduced such possibility. Based on our findings, we recommend authorities continue to, or increasingly, provide direct monetary incentives to purchase EVs, and to provide EV driving and riding experience to customers, especially who are in the middle- and low-income vehicle purchasing groups, to improve the Chinese EV market relative to CVs.

Keywords: electric vehicles; electric bikes; China; vehicle-purchase decision

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1. Introduction

Since 2003, more than 250 million passenger cars have been sold in China's domestic market [1–6]. By 2050, the total vehicle stock could be as large as 530 to 623 million vehicles [7]. It is predicted that these vehicles will consume up to an equivalent of 564 million tons of oil and will emit up to 1636 metric tons of CO_2 per year [8]. In 2012, China became the world's largest emitter of greenhouse gases (GHG) [9]. In June 2015, China set a target to lower the carbon intensity of its GDP by 60-to-65% by 2030, from its 2005 values [10]. A strategy for solving a series of energy and environmental issues appears to be the adoption of electric vehicles (EVs) over conventional vehicles (CVs). The Chinese government aims to curb GHG emission in the road transportation sector by promoting new energy vehicles (NEVs) and regulating vehicle fuel economy [11,12].

From 2010 to 2020, 4.92 million NEVs were sold in China, as shown in Figure 1 [1,6,13–17]. Although NEVs sales are increasing rapidly, the NEV market share was only 6.2% of the 20.18 million passenger cars sold in the domestic market in 2020. A large gap still exists between current NEV sales and stated goals [18]. Understanding potential consumers' attitudes and perspective towards NEVs (mainly battery electric vehicles [BEVs] or plug-in hybrid electric vehicles [PHEVs]) is important, because it not only will support the decisions made by the government and private sectors, but also contributes to decision-makers' overall understanding of market demand. A number of studies have pointed out how technological advancements and changes in policies may accelerate EV adoption in China [19,20]. Yet, as a country with a large percentage of e-bike users (over 250 million e-bikes have been sold since 1998 [3]), few studies have explored e-bike users' experiences and their influence on the purchase of EVs, the purchasing of which is beset by similar characteristics and barriers (i.e., range anxiety, charging). This question, lacking an answer in the literature, inspired us to conduct this study exploring the relationship between e-bikes and EVs, which may provide a new path to grow EV sales in China.

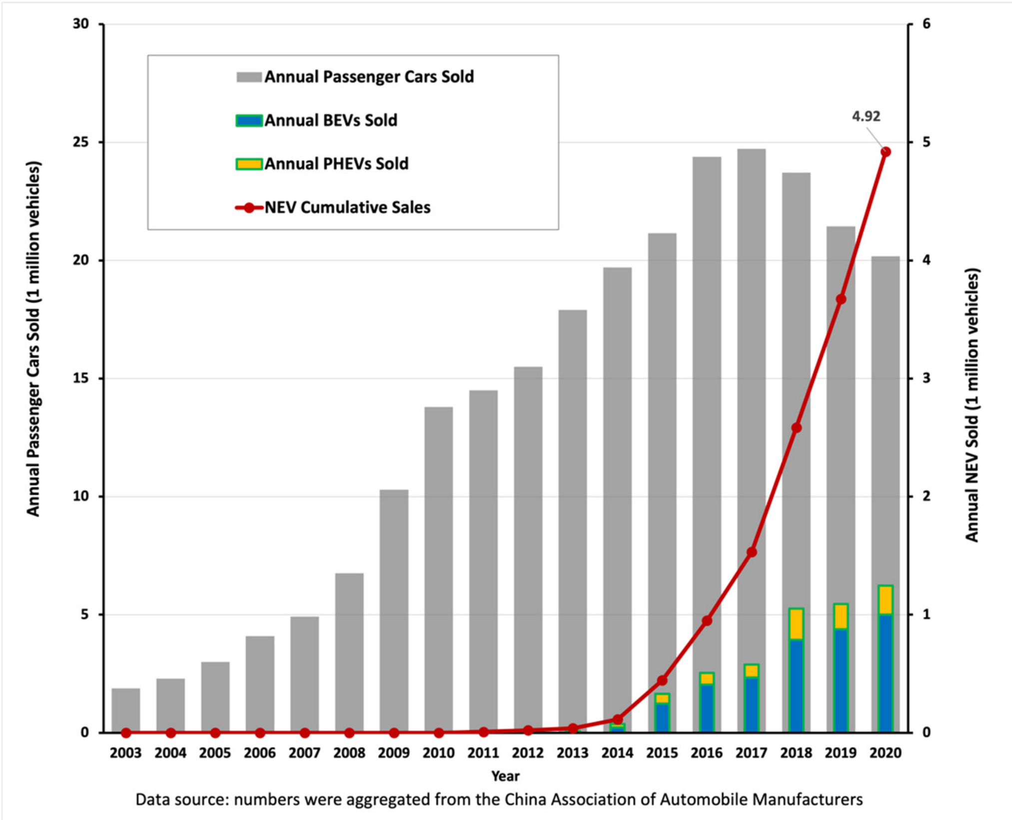

Figure 1. Conventional vehicles and NEVs sold in China since 2003.

This paper begins to fill an important gap by investigating purchasing intentions from customers' points of view and making policy recommendations based on the results. Specifically, this paper aims to answer the following questions:

1. How do respondents make purchase decisions among CVs, PHEVs, and BEVs?
2. Does experience with e-bike use have any influence (either encouraging or discouraging) on EV purchase decisions?

Focusing on how potential customers perceive BEVs and PHEVs and make purchase decisions, we surveyed 1216 respondents in Beijing, China. We constructed two models to answer the following questions: one to assess factors influencing all respondents' intentions to purchase a car in the near future, which is an extension of a 2015 study focusing on e-bike owners' car purchase intentions in 2013 [3]. The other model assesses factors influencing consumers' choices among CVs, PHEVs, and BEVs. The remainder of the paper is organized as follows: The Background section discusses government policies with regard to EVs, as well as previous studies on NEV purchase attitudes and factors influencing purchase intention. The Methods and Data section discusses the methodology and data collection used in the study. The Result, Analysis, and Discussion sections present our results and discuss EV purchase and policy implications. Finally, conclusions and limitations are presented in the Conclusions section.

2. Background and Literature Review

2.1. Government Policy

Since the turn of the 21st century, the Chinese government has launched comprehensive policies and incentives to promote development of the NEV sector [9,21,22]. Key policies related to NEVs are in accordance with the Chinese government's "Five-Year Plan". For example, under these policies, EV pilot studies were conducted in different cities and these pilot cities were able to set their own vehicle rollout strategies by following the basic guidelines ordered by the Central government. A list of key characteristics and milestones of EV development in China are summarized in Figure 2.

Figure 2. Major Chinese government NEV policies since 2002 (adapted from [22,23]).

Studies have also shown that, coupled with the gradual technological advancement of EVs and the appropriate set of EV promotion policies, the EV market is expected to grow in the coming future [24–27]. This speaks more to the importance of understanding the purchase behaviors of potential CV and EV drivers. In addition, in other developing countries such as Malaysia, it is shown that university students (a population that tends to adopt new technologies) who share an affinity for green consumption and green vehicles, are more likely to purchase green vehicles in the future [28]. Therefore, developing and promoting EVs not only holds domestic but international significance for China, as the country is seeking ways to grow sales and establish influence in international trade.

2.2. Past Work on EV Purchase Behavior

The growing literature on consumer EV adoption focuses on the different adoption behaviors of consumers towards EVs. Five theoretical frameworks have been identified: the framework of planned behavior and rational choice theory; a framework using normative theories and environmental attitudes; a framework emphasizing the role of symbols, self-identity and lifestyle; a framework considering the diffusion of innovation and consumer innovations; and a framework focused on consumers' emotions [29,30]. Since EVs currently have a low market share, studies of their adoption mainly focus on purchase intention [29].

2.3. New Energy Vehicle Attitude and Purchase Intention Studies

Previous studies have found that consumers' perceptions and acceptance of EVs, in addition to other factors, affect their purchase decisions. Representative studies of EV purchase intention in China are summarized in Table 1. This table shows data for the studies' samples, EV types, data collection, methodologies, and the aims of the studies. It also includes factors including demographic characteristic, perception and social factors, technological factors, policy related factors, and environmental influence. Stated preference (SP) survey methods are widely used to collect data. While previous studies explored customers' purchase intentions towards a wide range of NEVs, or focused on one type of electric vehicles, little is known about customers' more specific purchase inclinations towards BEVs and PHEVs, the two mainstream EVs in the market.

Table 1. Summary of similar studies of NEV perceptions and purchase intentions in China.

Authors	EV	Sample; Data Source; Methodology	The Aim of the Paper	Factors [1]				
				D	P	T	G	E
Zhang, Yu [12]	EV [2]	299 trainees in driving school; SP survey with questionnaires; binary logit model	To examine the factors that affect EV purchase time, and purchase price	√		√	√	
Zhang, Wang [31]	NEV [3]	349 potential consumers from auto dealers; SP survey; regression model	To identify purchase motivation and examine the impact of government policies	√	√	√	√	√
Li, Long [32]	NEV [3]	727 consumers from auto dealers; SP survey; four-paradigm model	To analyze consumers' evaluation of government policies				√	
Wang, Fan [33]	HEV [4]	433 consumers from auto dealers; SP survey; TPB, structure-equation model	To investigate consumers' intention to adopt HEVs	√	√			√
Li, Long [34]	BEV	940 consumers from auto dealers; SP survey; TPB, structure-equation model	To investigate household factors in BEV adoption	√	√			
He, Zhan [35]	EV [2]	369 responses; a web-based SP survey; TPB, structure-equation model	To explore the roles of perception and personality factors in EV adoption	√	√	√	√	√
Huang and Qian [36]	BEV, PHEV	348 responses; SP survey; nested logit model	To investigate the influencing factors in EV adoption in developing cities	√	√	√	√	
Yu, Yang [37]	EV [2]	157 samples; SP survey; system dynamics model	To understand the influence of government policies on EV adoption				√	
Lin and Wu [38]	EV [2]	988 samples; SP survey; ordered logit regression	To study the factors that influence public's EV purchase intention in Chinese largest cities	√	√	√	√	√
Habich-Sobiegalla, Kostka [39]	EV [2]	1080 respondents; A web-based SP survey; Ordered logit regression	To examine the factors of Chinese citizens' intentions to adopt EVs	√	√	√		
Sovacool, Abrahamse [40]	EV [2]	805 samples; a web-based SP survey; regression and principal component analysis	To examine the factors related to potential EV adoption	√	√	√	√	
Yang, Tu [41]	EV [2]	417 samples; a web-based SP survey; TPB, structure equation model	To analyze influencing factors in EV adoption		√			

Notes: [1] D = demographics and household characteristic; P = psychological and social status needs; T = technology, charging and vehicle performance; G = government policies and financial benefits; E = environmental concerns. √ = included in paper; blank cell = not included in the paper. [2] Electric vehicle (EV) is used in the paper without specific explanation of EV types. All the following EVs in this table refer to the general idea of electric vehicles. [3] New energy vehicle (NEV) without explanation or definition. [4] Hybrid energy vehicle (HEV) is defined as a vehicle that has both a conventional and an electric engine.

Five main studies have focused on the NEV market in China prior to our research design. A study conducted in Nanjing, China surveyed 299 highly educated, high-income students in a driving school to determine their acceptance of EVs, their anticipated purchase time and anticipated purchase price [12]. They found that, as EV technology improves, the market expands, and the government's policy and subsidy support continue, EVs could be popular among a broad population of people who intend to buy a car. Another study surveyed 349 potential consumers from automobile dealers from 13 cities in China to examine the impact of government policies [31]. In similar studies, household factors and government policy's influence on EV purchase were studied using empirical data from visitors to automobile dealers in China [32–34]. However, consumers who were contacted in automobile dealerships usually had pre-existing brand or model inclinations, as most 4S stores provide single-brand businesses, limiting customer exposure to a narrower range of EVs.

Since 2016, there have been more studies on different aspects of EV purchase behaviors in China. He, Zhan [35] conducted an online survey of 369 respondents and confirmed that personal innovativeness contributed positively to EV purchase. Huang and Qian [36] explored the EV market in lower-tier Chinese cities, suggesting that non-monetary policies may not contribute to the growth of EV sales. Meanwhile, a study by Yu et al. [37] in Shenzhen, one of China's most developed cities, revealed that non-monetary policies, such as driving restrictions on CVs, in addition to the expansion of charging stations in more places, would act positively to grow EV sales. To continue, a survey of four Chinese highly developed cities pointed to age (being younger) serving as a contributor to EV purchase [38]. They also found that government subsidies and concern for the environment mattered in preferences towards EVs. Habich-Sobiegalla et al. [39] investigated both the macro- and micro-level factors of EV purchasing and highlighted the role of personal social networks, as they found that knowing someone who owns an EV can positively influence one's decision to purchase an EV. Research by Sovacool et al. [40] confirmed the importance of previous experience with EVs, stating that it is a significant positive factor after controlling for other socio-demographic variables. Finally, Yang et al. [41] outlined the positiveness of knowledge of EVs in EV purchase willingness.

2.4. Factors Influencing New Energy Vehicle Purchase

Many studies discuss various factors contributing to stated EV purchase intention including; demographic and household characteristics, perception and social status, technological factors and performance, government policy and financial benefit, environmental concerns and infrastructure needs, as shown in Figure 3 [12,29,33,42–48].

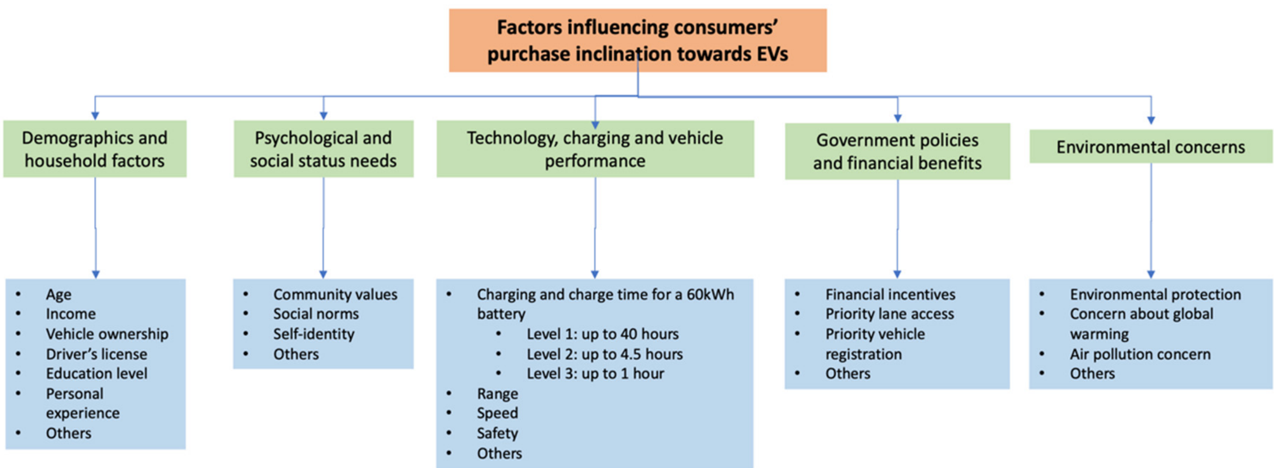

Figure 3. Factors influencing consumers' perception of EVs (the charge time information is referenced from [49]).

Consumers' impressions of NEV performance plays an important role in the purchase decision-making process [29,31,45,50]. Other researchers found, based on a UK survey of 1263 respondents, that performance considerations, such as comfort, noise, ease of driving, and automatic transmission were the most important factors affecting consumers' adoption of HEVs [51]. In another study conducted in the U.K., vehicle performance and range were important attributes largely because they are related to other attributes associated with owning and using EVs [50]. The result is consistent with a study in China that showed that a high degree of safety, quality, and good performance are key factors in the acceptance of EVs [12]. The available charging infrastructure is also of importance for EV adoption. For example, Javid et al. [52] found that PHEV adoption rate is positively correlated with per capita charging infrastructure. Other studies assumed the benefits of a widespread or properly distributed charging station network and proposed innovative approaches in management to optimize cost and the charging experience [53–57], which is hypothesized to retain and attract EV drivers. Respondents with pro-environmental self-identification are more inclined to have a positive perception of EVs [50,58]. Empirical research on EV acceptance reveals that consumers are concerned with financial benefit and think that EVs could reduce maintenance costs and improve fuel-efficiency, while some researchers found that the purchase price of EVs is the greatest determinant of EV purchase intention [31,59,60]. Fewer studies have addressed customers' attitudes and purchase intentions towards EVs in China. The ubiquitous experience of electric two-wheelers in China, in addition to scale and other unique attributes of China's transportation system, requires a focus on EV adoption, particularly the distinction between PHEVs and BEVs.

3. Methods and Data

3.1. Data Collection

In July 2015, an intercept survey was conducted in the five main urban districts of Beijing, including the Dongcheng, Xicheng, Chaoyang, Haidian and Fengtai districts. Although Beijing consists of 16 districts (Beijing Municipal Bureau of Statistics 2010), about 60% of the city's residents live in these five districts. The survey contained two parts. The first part included respondents' general understanding and attitudes towards electric vehicles, conventional vehicles, and e-bikes. To measure respondents' familiarity with EVs, respondents were asked to describe their understanding and knowledge of EVs. Then the trained surveyors rated respondents' familiarity level with EVs as "unfamiliar" (1), "somewhat familiar" (2) or "familiar" (3). There were four question categories in this part. The first category related to experience with EVs that included two binary questions. One question asked about if they had driven or ridden an EV prior to the survey and the other asked if they had friends or family members that owned an EV. The second question category concerned impressions of e-bikes and e-vehicles. We asked respondents to rate e-bikes and e-vehicles on an 11-point Likert-scale with -5 and 5 representing "very negative" and "very positive" ratings, respectively. The use of such a scale was inspired by Scherpenzeel [61], to improve data reliability and analysis. The third question category assessed levels of agreement about three statements. These were: (1) "Driving an e-bike improves my status or self-image.", (2) "Driving a CV improves my status or self-image.", and (3) "Driving an EV improves my status or self-image.". Respondents were asked to indicate their level of agreement or disagreement on these statements using a 11-point Likert-scale, from 0 to 10, with 0 indicating "totally disagree" and 10 "totally agree". Last, the fourth question category inquired about their vehicle purchase considerations using the same Likert-scale and attitude-assessment method as in the third category. Specifically, the following statements were presented: (1) "I would consider vehicle emissions when I plan to purchase a car", (2) "I have a positive attitude towards EVs because of e-bikes", (3) "Compared to a CV, an EV is similar in performance." (4) "Compared to a CV, an EV is cheaper over the long term." (5) "I (might) have more mechanical problems with an EV than a CV." (6) "I would prefer to drive a CV over an EV."

In addition, to understand the types of polices that may help drive EV growth, we asked the respondents to circle up to three EV policies that they would like to see from a range of provided options. There were 10 policy options to choose from, including: (1) purchase subsidies, (2) more changing stations, (3) free battery charging, (4) license-plate restriction waiver, (5) insurance benefits, (6) purchase-tax exemption, (7) license-fee exemption, (8) free parking, (9) Reserved parking spaces, and (10) Emission restriction.

The second part asked respondents about their demographics, their household vehicle ownership, their planned vehicle-purchase decisions, and their household vehicle-purchase history. In this part, we asked respondents if they planned to purchase a CV, PHEV, or BEV in the near future. We separated PHEVs and BEVs from the general notion of EVs to gain more insights into specific vehicle type and how different factors may influence their purchase decision. Respondents were surveyed at different locations in the districts, including malls, supermarkets, subway and bus stations and entertainment venues to obtain a wide range within the sample population. An intercept-sampling approach was used to randomly approach adults at each location as the potential research subject passed an arbitrary point. Data were collected in each district between 9:00 and 18:00 on multiple weekdays and weekend days. A pilot survey revealed limitations, particularly in the public understanding of questions related to hedonic and symbolic attributes. Also, because people have different opinions of EVs, since there are many different types of electric vehicles, such as electric buses and lightweight electric vehicles, surveyors were trained to explain these concepts carefully. These explanations were accompanied by an image of a conventional electric car to help explain.

After the removal of 1263 samples (46% of samples) lacking important information, such as household income and household vehicle ownership, 1216 surveys were analyzed. Cronbach's alpha was used to assess the internal consistency of the Likert-scale questions [62] and was computed by correlating the score for each scale item with the total score for each observation and comparing that to the variance for all individual item scores. A Cronbach alpha of $\alpha = 0.65$ was found in the study among the, which is considered acceptable [63,64].

3.2. *Future Conventional and Electric Vehicle Purchase Model*

Two models of household car purchase intention were developed: first, a model of car-purchase decision-making (i.e., whether to purchase a vehicle or not), and second, a model focusing on car-propulsion type (i.e., CV, BEV, PHEV). The selection of models is inspired by prior research in the same area [65,66].

3.2.1. Car Purchase-Decision Model

The first model aimed to understand car-purchase decisions. In our survey results, 38% of respondents intended to purchase a car in the two years following the survey, from 2015 to 2017, which is a significantly higher rate than the 21.4% of e-bike users whom we surveyed regarding car-purchase intentions in the national telephone survey we conducted in 2013 [3]. The dependent variable was purchase decision in the next two years, which is a binary variable. The independent variables were primarily the subjects' household characteristics. A binary logistic regression model is the most commonly used model in the literature for binary outcomes [67]. The distribution of plans to purchase a car showed significant variability in the five districts in Beijing that were surveyed ($p < 0.001$). A multi-level mixed-effect logistic regression model and a Bayesian multi-level logistic regression model were also utilized, taking districts as groups and households as the population. This allowed the examination of the effects of district-level and respondent-level variables on purchase decisions while accounting for the non-independence of observations within a cluster [68]. Compared to traditional regression models, Bayesian models assume that coefficients follow distributions rather than treating them as fixed values. Bayesian inference also overcomes the issue of overestimated odds ratios when the number of observations is limited [69]. The model specifications are shown in the following sections.

3.2.2. Binary Logistic Regression Model

The binary logistic regression model is described as follows:

$$logit\ (p(x)) = log\left(\frac{p(x)}{1-p(x)}\right) = \alpha + \beta_1 X_1 + \beta_2 X_2 + \ldots \beta_n X_n \tag{1}$$

$$p = \frac{exp(\alpha + \beta_1 X_1 + \beta_2 X_2 + \ldots \beta_n X_n)}{1 + exp(\alpha + \beta_1 X_1 + \beta_2 X_2 + \ldots \beta_n X_n)} \tag{2}$$

where p is the probability that respondents plan to purchase a car in the next two years (yes = 1, no = 0); α is a constant, β is the vector of parameters to be estimated, n is the number of independent variables, and X is the vector of independent variables collected in the survey and consisting of gender, education, job, household vehicle ownership, vehicle purchase history, number of licensed drivers, household income and other factors.

3.2.3. Multilevel Mixed-Effects Logistic Regression Model

The multinomial mixed-effects logistic regression model is described as follows:

$$logit(P_{ij}) = log\left(\frac{P_{ij}}{1-P_{ij}}\right) \tag{3}$$

$$logit(P_{ij}) = log\left(\frac{P_{ij}}{1-P_{ij}}\right) = \beta_0 + \sum_{m=1}^{M} \beta_m X_{m_{ij}} + Z_{ij} U_j \tag{4}$$

where p_{ij} is the probability of a car purchase decision of a household sample i (level 1)) in district j (level 2). X_{ij} are household features corresponding to fixed effects, while β_m are the coefficients of the model. Z_{ij} are the covariates corresponding to random effects. U_j represents a district-level random effect. The random effects are not directly estimated as model parameters but are instead summarized as variance components. The estimation of the parameters allows the correlations between households of the same district and between districts to be modeled. They are independent and assumed to be normally distributed: $U_j \sim N\left(0, \sigma^2\right)$ [70–72]. The maximum likelihood method was used to estimate the model. The data used in this study were organized into two levels. Level 1 is the household level, corresponding to household factors, with 1216 respondents collected in Beijing. Level 2 includes the five districts we covered and includes a dummy variable to represent one of the five districts in Beijing.

3.2.4. Bayesian Multilevel Logistic Regression Model

The Bayesian multilevel logistic regression model is described as follows:

$$logit(P_{ij}) = log\left(\frac{P_{ij}}{1-P_{ij}}\right) \tag{5}$$

$$logit(P_{ij}) = log\left(\frac{P_{ij}}{1-P_{ij}}\right) = \beta_0 + \sum_{m=1}^{M} \beta_m X_{m_{ij}} + Z_{ij} U_j \tag{6}$$

where p_{ij} is the probability of car purchase decision of the household respondent i (level 1) in district j (level 2). X_{ij} are household features to which correspond the fixed effects, while β_m are the coefficients of the model. Z_{ij} are the covariates corresponding to the random effects. U_j represents the district-level random effect. Four chains, each with 2000 iterations, were set up in Stan, a platform for high-performance statistical computation. In order to eliminate the influence of the starting values, the first 1000 iterations were set as a warm-up to calibrate the sample and were discarded from the estimate [73]. In the model estimation, with no prior knowledge of the value of the parameter for the district level, the prior was set as non-informative with a zero mean and a large variance, i.e., normal (0, 10^3). We used

Markov chain Monte Carlo algorithms, rather than traditional maximum log likelihood methods, to estimate the model.

3.2.5. Car Type Choice Model

The second model was of car propulsion-type (i.e., CV, PHEV, BEV) choice, developed with a multinomial logistic model, and estimate the attributes that would influence the vehicle-type purchase intentions of respondents who planned to purchase a car in the next two years, based on their stated preference survey result [67]. Among future car buyers (461 respondents) in our sample, 63% of them stated that they planned to purchase a CV, 26% were planning to buy a PHEV, and 11% planned to buy a BEV. The multinomial logistic model was formulated as follows:

$$P(i) = \frac{exp\left[\beta_{(i)} X_{in}\right]}{\sum_{\forall I} exp\left(\beta_{(i)} X_{in}\right)} \tag{7}$$

$$P(Y = 1) = \frac{exp\left(X\beta_{(1)}\right)}{exp\left(X\beta_{(1)}\right) + exp\left(X\beta_{(2)}\right) + \ldots + exp\left(X\beta_{(n)}\right)} \tag{8}$$

$$P(Y = i) = \frac{exp\left(X\beta_{(i)}\right)}{exp\left(X\beta_{(1)}\right) + exp\left(X\beta_{(2)}\right) + \ldots + exp\left(X\beta_{(n)}\right)} \tag{9}$$

where Y is the dependent variable, representing car type choice, including CVs, BEVs, and PHEVs. X is a vector of the possible variables, such as household characteristics, and personal inclination towards EVs. n represents the number of variables. $\beta_{(i)}$ is a set of coefficients corresponding to the ith choice.

4. Results and Analysis

4.1. Respondent Demographics and Perception of EVs

The data in Table 2 provide sample demographic statistics. Respondents were asked to select their household incomes from within income categories. The table also presents gender, age, income-per-person and the number of cars per person. Some information on the Beijing population is also provided in Table 2. However, since more detailed demographic data are not publicly available, we cannot claim that this is a representative sample of Beijing residents. Male respondents represent 58.6% of our sample, while the city data show fewer (51.4%). The majority of our respondents were between the 18–50 (88.8%) when surveyed, while seniors (60 years old or older) were under-sampled. For household income and car ownership, the distributions were similar. In addition, education levels cannot be compared due to the unavailability of city-wide data. Based on the available information, we noticed our sample was slightly younger and had more males compared to the city-wide data.

The average EV familiarity scores of respondents who intended to purchase a CV, PHEV, or BEV, and respondents who did not have purchase intentions were 1.80, 1.94, and 1.72 respectively, and statistically different between propulsion type (p = 0.022, EVs versus CVs; p = 0.000, EVs versus no purchase intention). This confirms that the Chinese public have different levels of understanding of EVs, which are still a quite new transportation mode in China. People who had an intention to purchase EVs were the group with a better understanding of EVs.

Table 2. Sample characteristics compared with Beijing city data.

Sample		Beijing City Data	
Category	**Percentage/Number**	**Category**	**Percentage**
Gender			
Male	58.6%	male	51.4%
Female	41.4%	female	48.6%
Age			
<18	4.9%	0–14	9.9%
18–50	88.8%	15–59	75.2%
≥51	6.3%	≥60	14.9%
Annual income per person (1000 Yuan)			
40.58		43.91	
No. of cars per person			
0.21		0.26	
Education			
Middle school or below	3.8%	-	
High school or technical school	25.2%		
Bachelor	58.0%		
Master's or above	13.0%		
Adults	3.5 (1.1)		
Children	0.6 (0.8)		
Number of licensed drivers	1.7 (1.0)		

Notes: Source: Beijing Economic and Social Development Statistics Year Book 2014, Beijing Statistical Bureau. Standard deviation in parentheses. $1 = 6.20 RMB (2015.6). Annual income per person of samples is estimated from mid-points of household income and household sizes.

Figure 4 shows household vehicle ownership, the parking situation among car owners, and car purchase intentions within the next two years. The first three categories show the number of cars, e-bikes, and motorcycles owned at the household level, respectively. We found that more than 70% of the respondents owned one or more cars in the household, 45% of households owned one e-bike or more, and only 24% of families owned motorcycles. The fourth category concerns the parking situation, both at home and at work, for those who owned a car. As depicted, for households with cars, their parking situations do differ. About 85% of the respondents parked their cars in a reserved parking space or shared parking space at home, and 78% parked in a reserved or shared space at work. Although in both situations they mainly rely on reserved and shared parking spaces, about 10% of households have mode dedicated parking spaces at home than at work. For those that do not have a dedicated parking space at work, they seem to utilize public parking lots as an alternative. This difference is likely due to the differences in charging between the home and workplace, as charging infrastructure is one of the primary barriers to electric vehicle adoption [18,74]. A reserved parking space at home or at work may be a suitable place for charging an EV. About 43% of the respondents do not have reserved parking spaces at home and work, which means these respondents may not have access to dedicated charging in their residential district or at work. As for car purchase plans, we observed that close to half of the respondents stated an intention to purchase a car in the next two years. Among them, most were considering buying a second car. In terms of car models, CVs were in favor, followed by PHEVs and BEVs, yet the overall preference of CVs over EVs was not huge.

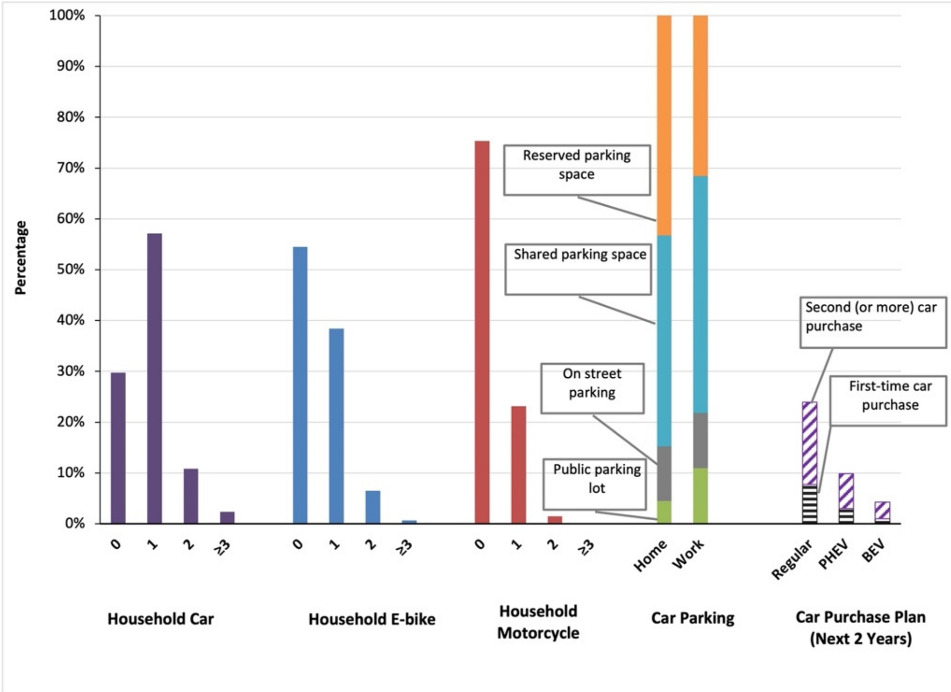

Figure 4. Household vehicle ownership, parking, and car-purchase intention over the next two years (sample sizes are 821 and 783 for parking at home, and parking at work, respectively).

Figure 5a shows respondents' first car and first e-bike purchase history. For cars, most car purchases happened between 2005 and 2015 (especially after 2010) at prices below 250,000 Yuan, corresponding to the rapid increase of motorization in China. However, some vehicle purchase prices did go up after 2010 as there are more higher-priced purchases compared to the past. For e-bikes, most purchases also occurred in the same period, likely echoing the effects of rapid motorization, with prices ranging from 2000–4000 Yuan. Of note, the Beijing government legalized licensed e-bikes for travel within the city in 2006. Fueled by the maturation of e-bike technology from 2005 to 2010, it may explain the increased popularity among e-bikes in the city that was surveyed. As for e-bike purchase price, we also notice an overall increase in the average price, with more models sold at a higher price compared to the early stage.

Figure 5b shows respondents' purchase budget for their proposed car purchase. The percentiles and the average budget for the three different vehicle types appear to be interesting. Specifically, when comparing the average (mean) purchase budget, people are more willing to pay more for PHEVs (218,583 Yuan), than CVs (197,973 Yuan) and BEVs (166,346 Yuan). The median (50% percentile) tells the same story. However, the maximum willingness to pay is higher for CVs, while the minimum willingness to pay is higher for both EV models. These may jointly suggest that on average, PHEVs are more attractive than CVs at the same price. However, there do not seem to be high-end products for EVs (especially for BEVs), or they have been poorly advertised. Between EVs, PHEVs are preferred. In the Chinese context, low-end BEVs may be considered as inferior to PHEVs and CVs, likely due to their close technological relationship with e-bikes, which may be considered an immediate alternative in lieu of owning a car. This is in great contrast to the developing world, where BEVs are viewed as high-end or even luxurious products.

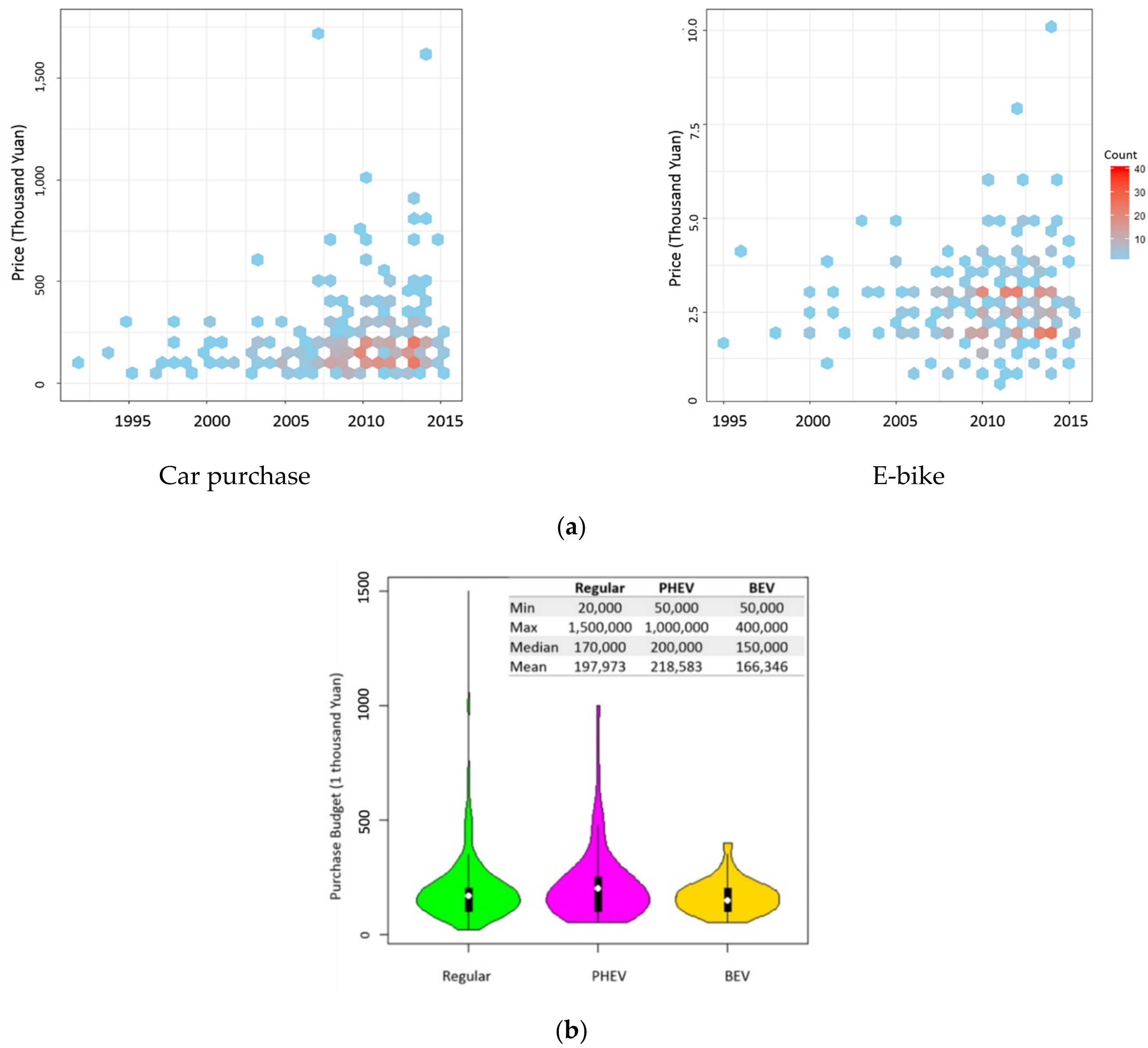

Figure 5. Vehicle purchase history (**a**) and future purchase budget (**b**).

Table 3 and Figure 6 show potential consumers' understanding and attitudes towards EVs, including experience with EVs, general ratings, social norms, and consideration of purchase. Experience with EVs contributed to a higher likelihood of EV purchasing (p-value = 0.010). The neighbor effect was found [75] for the potential EV-purchase group compared to CV-purchase or no-purchase groups (p-value = 0.010, and 0.000 respectively). The group interested in CVs rated the EVs the lowest (1.91) among the three groups, statistically lower than the 2.36 of the EV-purchase group (p-value = 0.036), suggesting image of EVs should be promoted to attract CV customers.

Table 3. Consumers' understanding and attitudes towards EVs.

No.	Category	Question/Level of Agreement on Statement	Mean			ANOVA Test		
			EV	CV	No	EV vs. CV	EV vs. No	Within Group
Q1	Experience with EVs	Have you ever driven or ridden in an EV? (Yes = 1, No = 0)	0.45	0.38	0.34	0.128	0.007 ***	0.024 **
Q2		Do you have friends/family or neighbors that own an EV? (Yes = 1, No = 0)	0.53	0.41	0.38	0.010 **	0.000 ***	0.002 ***
Q3	General rating	[a] What is your impression towards e-bikes in general?	1.87	1.81	2.00	0.795	0.532	0.492
Q4		[a] What is your impression towards e-vehicles in general?	2.36	1.91	2.20	0.036 **	0.374	0.064 *
Q5	Social norm	[b,c] Driving an e-bike improves my status or self-image.	4.45	4.65	4.55	0.468	0.658	0.749
Q6		[b,c] Driving a CV improves my status or self-image.	5.60	6.06	6.02	0.032 **	0.023 **	0.056 *
Q7		[b,c] Driving an EV improves my status or self-image.	6.81	6.27	6.33	0.013 **	0.012 **	0.026 **
Q8	Purchase consideration	[b,c] I would consider vehicle emissions when I plan to purchase a car.	7.52	7.31	7.48	0.439	0.859	0.589
Q9		[b,c] I have a positive attitude towards EVs because of e-bikes.	6.51	6.21	6.27	0.269	0.304	0.494
Q10		[b,c] Compared to a CV, an EV is similar in performance.	6.23	5.80	5.72	0.102	0.019 **	0.069 *
Q11		[b,c] Compared to a CV, an EV is cheaper over the long term.	7.36	7.15	6.98	0.433	0.088 *	0.198
Q12		[b,c] I (might) have more mechanical problems with an EV than a CV.	6.25	6.20	5.87	0.842	0.070 *	0.073 *
Q13		[b,c] I would prefer to drive a CV to an EV.	5.06	6.10	5.45	0.000 ***	0.094 *	0.000 ***

Notes: [a] Eleven-point Likert scale, −5 to +5; −5: very negative; 0: neutral; +5: very positive. [b] Eleven-point Likert scale, 0 to 10; 0: strongly disagree; 10: strongly agree. [c] Questions were asked in the following form: "To what extent do you agree with the following statement?" ***, **, * denote the statistical significance of the estimate at the 1%, 5%, and 10% levels.

The social status of operating an e-bike, a CV or an EV was assessed (Table 3). The EV-purchase group rated a significantly lowest social status score to driving CVs (5.60) but the highest for driving EVs (6.81). No statistical significances were found regarding emissions or positive attitude towards e-bikes, though the scores were higher for the EV-purchase group. In addition, the EV-purchase population had the statistically highest agreement that EVs are similar to CVs in performance (p-value = 0.019). Meanwhile, the CV-purchase population agreed that they preferred to drive a CV over an EV, with statistical significance (p-value = 0.0000).

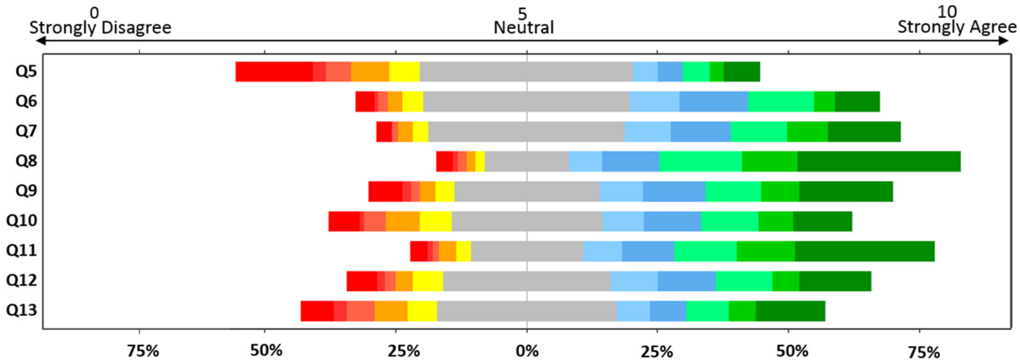

Figure 6. Level of agreement on social norm and purchase consideration statements.

4.2. Model Results

The car purchase-plan model results are presented in Table 4. The three models' results were very close, as can be seen by checking their coefficient estimates. Concerning interpretability and model performance, we focused on the multilevel mixed effect logistic regression model. The estimated results were generally intuitive and mostly consistent with other Chinese studies on car-purchase behavior, with some new and interesting findings. Household income, and the duration of ownership of one's first motorized vehicle (e-bike/motorcycle/car) were both positive and significant (p-value = 0.001 and 0.001, respectively). This finding is partially in line with the findings of Li et al. [34]. In their structural equation model analysis, they identified income as a positive factor in EV adoption but existing CV ownership as a negative contributor. In our study, the household number of e-bikes was insignificant, while the number of motorcycles was significant and positive (p-value = 0.022) and the number of cars was significant and negative (p-value = 0.007). Besides, families with no motorized vehicles were most likely to purchase a car, followed by families who purchased e-bikes as their first motorized vehicle, compared with families who had motorcycles or cars as their first motorized vehicles. It is likely that, in our model, the positive effects of motorcycles overwhelmed the negative impacts of CV ownership, or that these effects vary over time. The more cars a household owned, the lower their probability of purchasing a new one. However, the more motorcycles a household owned, the higher their probability of purchasing a car, due to the household becoming more motorized. This may suggest that motorcycle owners tend to move to heavier motorized vehicles to replace current vehicles or to supplement current travel demands.

Table 4. Models' results for purchase plan.

Logistic Regression Model	**Binary**		**Multilevel Mixed Effect**		**Multilevel Bayesian**	
Factors	**Coef.**	***p*-Value**	**Coef.**	***p*-Value**	**Coef.**	**95% Credible Intervals**
			Fixed Effects		Population-Level Effects	
Constant	−2.71	0.00	−2.20	0.00	−2.57	(−3.82, −1.68)
Gender (Male = 1, Female = 0)	0.35	0.01	0.34	0.01	0.34	(0.07, 0.61)
Driver license						
Already have license	1.66	0.00	1.66	0.00	1.62	(1.14, 2.13)
Plan to get license	1.10	0.00	1.11	0.00	1.06	(0.55, 1.58)
No plan at all	base		-	-		
Emission concern (Not Concerned = 1, ... Very Concerned = 10)	−0.13	0.36	−0.13	0.37	−0.13	(−0.41, 0.14)
No. of licensed drivers	0.15	0.06	0.15	0.06	0.16	(0.00, 0.32)
Household income	0.03	0.00	0.03	0.00	0.03	(0.02, 0.05)
No. of e-bikes	0.12	0.38	0.11	0.40	0.13	(−0.07, 0.33)
No. of motorcycles	0.34	0.02	0.34	0.02	0.19	(−0.06, 0.44)
No. of cars	−0.34	0.01	−0.33	0.01	−0.39	(−0.62, −0.18)
Duration of first motorized vehicle ownership in months	0.06	0.00	0.06	0.00	0.04	(0.01, 0.08)
E-bike is the first motorized vehicle (Yes = 1, No = 0)	−0.48	0.10	−0.48	0.10	−0.47	(−1.04, 0.09)
Motorcycle is the first motorized vehicle (Yes = 1, No = 0)	−0.96	0.01	−0.94	0.01	−0.93	(−1.61, −0.27)
Car is the first motorized vehicle (Yes = 1, No = 0)	−0.54	0.05	−0.54	0.05	−0.54	(−1.08, 0.01)
District			Random effects		Group-level effect	
1	Base		Intercept of District		Intercept of District	
2	0.44	0.03	Variance	Std. dev.	Variance	
3	0.94	0.00	0.09	0.08	0.38	(0.15, 2.51)
4	0.96	0.00				
5	0.38	0.04				
Goodness of fit	LR chi^2 = 148.67 $p > chi^2 = 0.001$		Wald chi^2 = 105.83 $p > chi^2 = 0.000$		Rhat of each parameter: 1	
BIC	1594.1		1586.1			

In addition, males were more likely to purchase a car in the next two years, which differs from the findings of Li et al. [34]. It is possible that the inconsistency in the effects of gender across studies is due to the fact that car purchase is often a household decision, whereas respondents in these surveys were individuals who may only have expressed their own views, which could have been in conflict with other household members. Respondents who already had a driver's license or planned to have one were significantly more likely to have vehicle-purchase plans (p-value = 0.000 for both). The number of driver's licenses was significant at the 90% confidence level (p-value = 0.06 for both), agreeing with Zhang et al. [12]'s finding. With consideration to random effects, the standard deviation of the intercept at the district level indicated that car-purchase fixed effects had little variation across districts.

The car propulsion-type choice model's estimates are presented in Table 5. The car propulsion-type choice model was determined based on the answer about which types of cars would be purchased (with three possible outcomes: CV, PHEV, and BEV) if the household planned to purchase a car in the next two years (i.e., 38% of our all respondents). Among our respondents, 24% planned on purchasing a CV, 10% a PHEV, and 4% a BEV. Of the sample size of 464 persons, Table 5 shows the 38% of the respondents who stated an intention to purchase a vehicle. In the model, CV purchase intention was set as the reference group. We found that being a male and having a higher household income contributed to a higher chance of intending to purchase PHEVs and BEVs, consistent with both of our car purchase-plan models. We also found that prior experience with EVs contributed to a higher likelihood of purchasing BEVs, echoing Sovacool et al.'s [40] research. However, a pre-existing inclination towards CVs, planning to have a driver's license in the next three years, longer ownership of one's first motorized vehicle significantly decreased likelihoods of intending to purchase PHEVs, while possession of a driver's license and a large purchasing budget decreased the likelihoods of intending to purchase BEVs. Of note, some of these effects cannot be verified by other studies since some of the examined variables have not been included in the existing literature.

Table 5. Multinomial logit model results of car type choice behavior.

Factors	**Coefficient**	**Std. Err.**	***Z*-Value**	***p*-Value**
CV	Base outcome			
PHEV				
Gender (Male = 1, Female = 0)	0.40 *	0.26	1.56	0.120
Personal inclination to CV (Likert-scale, Not at all: 0, . . . , Definitely yes: 10)	−0.08 **	0.04	−1.85	0.064
Plan to have a driver's license within three years	−0.87 *	0.58	−1.50	0.135
Household income (in 10,000 Yuan)	0.22 ***	0.09	2.37	0.018
No. of e-bikes	0.37 **	0.20	1.85	0.065
Duration of first motorized vehicle ownership (years)	−0.04 *	0.03	−1.50	0.134
First motorized vehicle was a motorcycle (yes = 1, no = 0)	0.72 *	0.46	1.55	0.121
Constant	−1.42 *	0.88	−1.62	0.105
BEV				
Gender (Male = 1, Female = 0)	0.99 ***	0.40	2.47	0.013
Personal inclination to CV	−0.20 ****	0.06	−3.32	0.001
Drive or ride EV before (Yes = 1, No = 0)	0.94 ****	0.35	2.71	0.007
Already have a driver license	−1.34 **	0.70	−1.91	0.056
Household income (in 10,000 Yuan)	0.53 ****	0.15	3.48	0.001
Purchase budget (in 1000 Yuan)	−0.01 ***	0.00	−2.51	0.012
First motorized vehicle was a car (Yes = 1, No = 0)	0.64	0.44	1.44	0.150
Constant	−2.70 ***	1.23	−2.20	0.028
LR chi^2 (22) = 39.54	Prob > chi^2 = 0.000			
Log likelihood at convergence = −371.593	Sample size: 464 (38% of the respondents who stated an intention to purchase a vehicle)			

**** Denotes estimate is statistically significant at the 1% level. *** Denotes estimate is statistically significant at the 5% level. ** Denotes estimate is statistically significant at the 10% level. * Denotes estimate is statistically significant at the 15% level.

More importantly, we found that e-bike ownership would positively contribute to the potential purchase of PHEVs but not BEVs, which has not been revealed by the existing literature. We consider this as our major theoretical contribution to the existing literature of e-bikes and EVs. E-bikes, despite their adoption growing rapidly in China, are relatively low-cost and used by the carless, low-income groups. This may generate a below-average image for EVs, which use similar battery and charging technologies [76]. China has an abundance of very low-cost mini-EV cars that are generally of low-cost and low-quality, by international standards [77]. It is likely that the potential Chinese EV buyers' value EVs as a low-end product based on their perception of e-bikes, which could be further investigated in future studies. Contrarily, however, familiarity with the battery and charging technologies among e-bike users may instead contribute to EV adoption, given that China is experiencing a rapid rise of motorization and these carless e-bike users are becoming wealthier. In our study, the result of e-bike ownership being positively correlated with the potential purchase of PHEVs but not BEVs shows that our speculation may be correct, as e-bike owners were concerned with issues that are shared between e-bikes and BEVs (e.g., range anxiety). In comparison, these issues are advantages in the perception of PHEVs, as the range-anxiety problem is addressed. While providing a similar driving and ownership experience to CVs, PHEVs can be more attractive, benefitting from EV's conceptualizations.

During the COVID-19 pandemic lockdown in China, when healthcare professionals and essential workers were using electric scooters (e-scooters), another form of general low-cost electric technology in China, to travel within the city when public transportation was shut down, these new technologies were massively covered by the Chinese media and may have changed impressions of EVs or BEVs for some Chinese customers, since these e-scooters are efficient and can allow social distancing. In addition, Wen et al. [78] reviewed the changes in the EV market in China after the pandemic and suggested that the EV industry is likely to reform, which may provide a better opportunity for EV growth, since smaller EV brands that manufacture low-cost EVs may be replaced by or integrated into bigger brands. Therefore, it is not surprising to see a positive role of e-bikes in BEVs in the future.

4.3. Policy Implications

Respondents were asked to choose three preferred EV promotion policies among the ten possible policies we provided. The results are shown in Figure 7. Of the respondents, 52% chose purchase subsidies and more charging stations, indicating that the public prefers direct-purchase cost reduction or monetary subsidy and more advanced infrastructure service. This aligns with other studies [37,38]. Currently, both central and local governments provide one-time purchase subsidies to EV buyers. Free battery charging was ranked third among possible promotional policies. However, although free battery charging may be effective in promoting EVs for a short period, it may not be a sustainable long-term strategy, as technologies are still developing.

The next-highest result, at 34%, was the choice of license plate-restriction waivers, confirming the findings of Yu et al. [37]. Beijing has been using traffic restrictions based on the last number of license plates for ten years, to reduce the number of car trips and shift travelers toward public transit. License plate-restriction waivers can be a good way to grant an advantage to EVs, but they undercut the original purpose of congestion mitigation. CV insurance benefits, purchase-tax exemptions, license-fee exemptions and free parking ranked fifth through eighth, respectively. Only 19% of the respondents chose reserved parking spaces, and 8% chose emission restrictions.

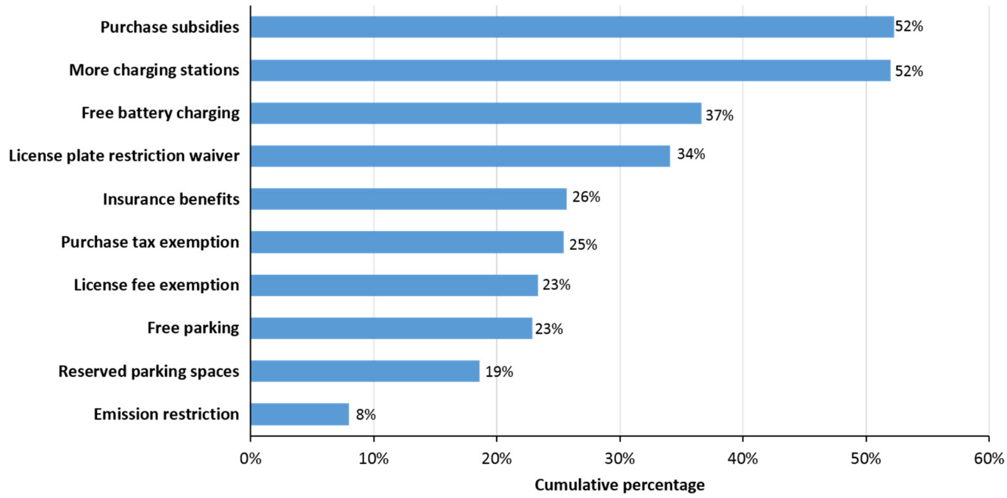

Figure 7. Preferred top-three EV-promotion policies.

We also found that future EV customers are only willing to allocate a relatively low budget to potential BEV purchases, probably because they are concerned about the potential risk of immature EV technologies and services, though they may also have low expectations because of their experiences with low-cost e-bikes. We suggest that the EV market, especially the BEV market, should target the mid-level-and-below markets, in addition to the top-end market. The mid-level-and-below markets for EVs could encourage more future CV customers with relatively low budgets to lean towards EVs if central and local government subsidies are in place.

The experience of having previously ridden or driven an EV through demonstration programs had a statistically positive influence on BEV-purchase intention. Although over 25 Chinese cities have had pilot EV projects, more pilot or demonstration projects are recommended. Also, test-driving and EV-sharing are also likely to benefit EV perceptions. With more Chinese cities and drivers adopting EVs, exposure to EV experiences from riding a taxi or a ride-hailing vehicle can be increased. For example, Shenzhen, a highly developed city in China, has switched to EVs for all city taxis while many other Chinese cities are gradually following this move.

4.4. Limitations

Some limitations to this study have been identified. First, the sample size is limited to respondents from Beijing, which did not allow us to estimate different local government policies or the general public's attitude and intention toward buying EVs. This sample may also suffer from representativeness issues, as we sampled more male and younger respondents than are reflected in the city's demographics. This is a group that is likely to prefer new technologies such as EVs and relevant promotion policies. Second, we did not survey or evaluate respondents' different perceptions of PHEVs and BEVs in Likert-scale question form because of survey-length limits and time constraints. In addition, we had a relatively low Cronbach's alpha of 0.65, for to the same reason. A low Cronbach's alpha may occur when the questionnaire suffers from internal inconsistency or when there are fewer questions than would be ideal. These factors may have affected our findings. Fourth, we chose an eleven-point Likert-scale in our study, which may produce different conclusions when compared to other scales, such as a five-point scale. Fifth, our sampling approach was non-random intercept, which may have introduced biases. Last, there are many other factors that influence people's choices besides the attributes themselves, which is generally challenging for models, including ours, to capture.

5. Conclusions

EV ownership is growing rapidly in China. This paper adds to the growing body of literature investigating vehicle purchases in the Chinese context. There are three main contributions of our paper. First, we are among the few papers to conduct in-person surveys to understand EV-purchase willingness among Chinese citizens, whereas most similar studies have relied on online surveys. Due to this, we may have overcome the sampling issues of online surveys, and have provided a different source of reference for the topic of interest. Second, instead of modeling EVs as a general notion, we differentiated both PHEVs and BEVs from EVs in our questionnaire and modeling. This allowed us to understand the differences in the driving factors of the adoption of different models of EVs in greater detail. Third and most importantly, we attempt to investigate the relationship between e-bike experience and EV- (PHEV or BEV) purchase intention, which has not been fully investigated by previous studies. Given our previous research experience with e-bikes, we hypothesize that e-bike experience can influence EV purchasing because of the similarities therebetween, such as range anxiety and battery charging. Our study provides evidence supporting this argument, as e-bikes were found to positively influence PHEV purchase, but not the purchase of BEVs.

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