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Why people want to buy electric vehicle: An empirical study in first-tier cities of China

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ABSTRACT

Electric vehicles are considered to be one of the most important ways for China to solve a series of energy problems such as urban smog, energy supply security and turning to green development. With the powerful support provided by the government, China has become the world's largest electric vehicle market and continues to maintain a high-speed growth. This paper examines the factors that may affect the public's purchasing intention of electric vehicles via a survey. An electric vehicle purchasing intention model is proposed based on the literature review and the reality in China. The model takes into consideration a number of demographic characteristic factors and attitude factors. A survey was conducted in China's four largest cities which include: Beijing, Shanghai, Guangzhou and Shenzhen. Based on the survey data, the paper examines the public's cognition of each influencing factor and analyses the impacts of these factors. The results reveal that attitude factors such as network externality, price acceptability, government subsidies, vehicle performance, environmental concerns, and demographic characteristics such as gender, age and marital status have significant impact on respondents' willingness to purchase electric vehicles. The finding of this paper provides constructive advices to diverse stakeholders.

1. Introduction

Air pollution has become a serious problem in urban areas of China. Especially in the large cities, highly concentrated contaminants, including airborne particulate matter, SO_2 and NO_X, have caused millions of people to die every year (Rohde and Muller, 2015). Smog is the most familiar form of air pollution, which is now one of the most important public concerns in China. In the Hazardous smog days, the government often issues "red alert" and impose regulatory measures such as traffic restrictions based on even and odd numbered license plates. Emissions generated by driving vehicles are considered to be a critical factor causing the smog pollution (Zhang et al., 2014; Huang et al., 2016). Vehicle ownership of China has grown rapidly in recent years (Lin and Du, 2015). As shown in Fig. 1, the vehicle ownership in China has growth more than 100 times since 1980, while the population only increase 40% during the same period. Since 2009, China has overtaken the US in terms of total vehicle production and has become the largest automotive market in the world (Liu et al., 2010). In 2015, the total sales amount reached to 24.6 million vehicles in China. Meanwhile, motor vehicles consume nearly 40% of oil used in China (Lin and Xie, 2013). If the oil consumption rate of vehicle rises to the level of United State, which is as high as 70% (Davis et al., 2016), China may consume more than 1 billion ton oil per year. The rapid and sustained growth of vehicle energy consumption has raised concerns over local air pollution, carbon dioxide emissions, and national energy security (Yin et al., 2015; Du and Ouyang, 2017). If no restrictions are exerted to the use of vehicles in China, the support of such large energy consumption may be unsustainable in the future years (Wang et al., 2014).

The adoption of electric vehicles (EV), which is considered as the main trend in the future's development of China transportation sector, is now implemented as a long-term solution to the problems mentioned above. Benefiting from the powerful supports offered by the government, China is now the largest EV consumer and manufacturer in the world. Table 1 lists the sales number of new energy vehicle (NEV) and EV of China in recent years. The NEV market of China is often segmented into EV, plug-in hybrid vehicle (PHEV) and others like fuel cell vehicle (FCV) and capacitance vehicle (CV). Most of the market share is occupied by EV which is powered solely by electricity and the PHEV which having both electric motor and internal combustion engine. Presently, support policies in China are focused on the EV market and

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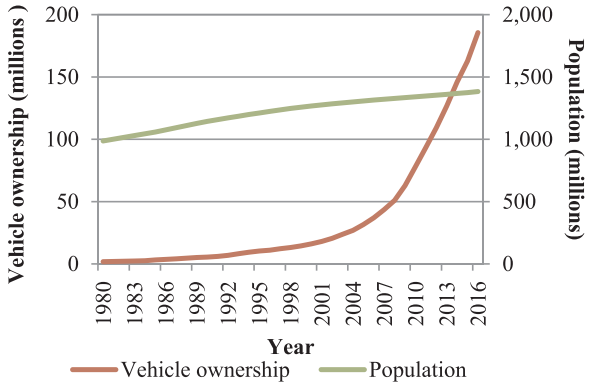

Fig. 1. Trend of vehicle ownership and population in China.

most of the NEV sales in China are pure EV now. The booms of NEV /EV market started in 2014, when the sales growth recorded a number higher than 200% at that year. The increasing momentum maintains in the following years and shows no signs to let up. Meanwhile, the proportion of EV sales has grown to 1.43% from a negligible level. An ambitious program proposed by central government plans that the ownership of EV may reach more than 5 million by 2020.

There are two reasons for the fast growth of EV. One is that, the China's government releases a new subsidies policy in 2013, which greatly enhance the subsidies for the EV. Another is that the price of battery, which is one of the major costs of EV, has declined to the range of economic feasibility (Lin and Wu, 2017). The subsidies are only for the EV, and other NEVs such as PHEV are excluded. As a result, most of the NEV market is occupied by EV.

China's consumers have shown a high willingness to adopt EVs (Helveston et al., 2015). If the present policy is maintained, the demand for EV may still maintain a rapid upward trend and begin to be an available alternative for gasoline vehicles. Therefore, to understand what factors may impact the purchasing intention of EVs is important for the government and industry. First of all, the government can release a more efficient policy to provide subsidies and promote the growth of EV. Secondly, the public may have cognitive bias about EVs, which may affect the purchase intention. A better understanding about these biases may help the industry to plan a more efficient market strategy. Thirdly, according to the public's attention, the manufacturers can centralize the resources in the points which may have stronger influence on the EV demands.

Though China is now the largest EV market in the world, previous studies on the topic of EV in China mainly focus on the influence of power grid (Gao and Zhang, 2011; He et al., 2016), the public infrastructure of charging system (Andrenacci et al., 2016; Moon and Kim, 2017), and the subsidy policy (Hao et al., 2014; Zhang et al., 2016; Diao et al., 2016). Few studies focus on what factors impact the purchasing intention of China's vehicle consumer.

This paper proposes an integrated model to evaluate the acceptance of EV. A survey is designed and conducted to collect empirical data about the factors that may influence the purchasing intention about EVs; quantitative analyses of these factors are also implemented.

The remainder of this paper is arranged as follows: Section 2 briefly reviews the previous literature, followed by a theoretical framework and data sources in Section 3. Section 4 provides descriptive statistics of the samples, and Section 5 presents the main findings of the survey and the discussion about the result. The policy implication and conclusion are presented in Section 6 and Section 7.

2. Literature review

Literature on EV adoption has grown dramatically in recent years (Rezvani et al., 2015). This selective review focuses on the adoption behavior and attitude factors for the purchasing intention of EVs.

The theory of planned behavior (TPB) is frequently used to predict the intentions of consumers. The TPB assumes that the decision is made based on rational evaluation of stimuli; human action is guided by behavioral beliefs, normative beliefs and presence factors (Ajzen, 1991). Consumer's behavior is directly predicted by intentions, and the intentions can be predicted by the sum of possible consequences of behavior (Bamberg and Möser, 2007). Rezvani et al. (2015) review the literature about the adoption of EVs, and found that various models have been established based on TPB theory. The example including Moons and De Pelsmacker (2012) applied TPB to investigate the determining factors of the usage intention of an electric car and identified some correlated factors. Sang and Bekhet (2015) extended the framework of TPB to explore EVs acceptance in Malaysia, and found seven key predictors to be statistically significant towards electric vehicles usage intention.

The TPB proposed that the behavioral intention is formed by the attitude, subjective norm and perceived behavioral control. We can expand the intention by incorporating variables (Sang and Bekhet, 2015). According to the previous empirical study, we can categorize the factors as follows:

Some researchers proposed that the demographic variables, such as age, gender, education level and income, may impact the perceived behavioral control, and will influence the intentions of adoption (Liu et al., 2013; Axsen and Goldberg, 2016).

The charging infrastructure may also influence the perceived behavioral control. Egbue and Long (2012) pointed out that the charging infrastructure is now one of the major challenges faced by EVs. Neubauer and Wood (2014) found sufficient charging infrastructure will reduce the range anxiety, which may significantly affect the usage intention of EVs.

The TPB considers that individuals may relevant others' beliefs that he or she should or should not perform such behavior. The social influence occurs when individual's emotions, opinions, or behaviors are affected by others. Axsen et al. (2013) point out that the battery electric vehicle (BEV) perceptions of people were “highly influenced” by at least one social interaction. Kelman (1958) identified three broad varieties of social influence: Compliance, Identification, and Internalization. Sang and Bekhet (2015) figured out that the interpersonal influence may impact the social influence and affect the usage intention of EVs. Eppstein et al. (2011) applied the agent-based model to study market penetration, and modeled network externalities based on an agent's susceptibility to media campaigns and social influence when studying the adoption of EVs.

The attitude toward behavior may be affected by behavioral beliefs

Table 1
Sales of new energy vehicle in China.

Year	2011	2012	2013	2014	2015	2016
New energy vehicle[a]	8159	12,791	17,642	74,763	331,092	493,806
Electric vehicle	5579	11,375	14,604	45,048	247,482	400,916
Overall vehicle	18,505,114	19,306,435	21,984,079	23,491,893	24,597,583	28,028,175
EV proportion	0.03%	0.06%	0.07%	0.19%	1.01%	1.43%

[a] The sales number of new energy vehicle include the electric vehicle and other type of vehicle such as PHEV, FCV and CV.

and outcome evaluation. For the EV, this may include concerns about environment, financial benefit and satisfaction about the subsidies. EV adoption is often considered as an environmental protection action and may be affected by the environmental concerns (Rezvani et al., 2015). Yadav and Pathak (2016) concluded that the environmental concern emerged as the most significant predictor of green purchase intention. Krupa et al. (2014) shows that those who are most concerned about climate change have a greater willingness to consider purchasing EVs. This is consistent with other studies in which people who believe that a pro-environmental self-identity fits with their self-images are found to be more likely to have positive perceptions of EV attributes (Schuitema et al., 2013).

Zhang et al. (2013) studied the private purchasing behaviors of NEVs in China and figured out that the financial benefits are an important motive for individual consumers to purchase EVs. Cost factors like the purchasing price could become more important in the practical stage of EV application (Klöckner, 2014). Barth et al. (2016) find that the purchasing price is the most important factor related to adoption of EVs. However, according to the finding of Dumortier et al. (2015), consumers do not appear to respond to the fuel expenditure in their preference rankings about EV though the five-year fuel expenditure savings are large. In addition, Matthews et al. (2017) found that the unavailability of EVs and a long waiting period to receive the vehicle was a major barrier for the consumer's purchasing intention, and the sales sometimes might send inaccurate information to the buyers.

Among all the policy instruments, purchase subsidy plays an essential role in launching the EV market (Hao et al., 2014). Zhang (2014) researched the effect of consumer trade-offs and government subsidies, and found that subsidies help decrease the EV breakeven quantity and offset the influence of loss aversion. Sierzchula et al. (2014) analyzed electric vehicle adoption of 30 countries and found the financial incentives are statistically significant factors.

3. Methodology and data

3.1. Backgrounds

In order to deal with the urban smog problem and encourage green development, the central and local governments of China have prioritized the development of EVs and promulgated a series of policies from the perspectives of sustainable development including fiscal subsidies and tax incentives (Yuan et al., 2015). Table 2 lists some subsidy policy of EVs in the level of central government and local governments. The relevant policies can be summarized as the following:

- The government provides direct subsidy for the purchase of EVs. According to the driving mileage of vehicles, the purchaser can receive as much as 25,000–55,000 CNY (about 3800–8400 US Dollar) in subsides from the central government, and many local governments provide additional subsidies. Some EVs can receive a total subsidy up to 110,000 CNY per vehicle when purchasing some model of EVs. The subsidies can reach 25–60% of the purchase price of the vehicle.[1]
- Tax deduction and exemption are implemented in EV trade. The central government has exempted the purchase tax of EVs, which may account for 10% of the sale price. Some local governments have additional policies such as exempted vehicle and vessel tax and toll charge.
- Some cities applied license plate lottery for vehicles aiming to limit the amount of vehicles and curb congestion. To promote the use of electric cars, a lot of cities provide priority for the purchase of EV. EV purchaser will not have to go through the license plate lottery that is applied to gasoline cars. Beijing allows unlimited purchase of battery-electric vehicles. Green cars in Shanghai can get a free license plate, which is worth more than 80,000 RMB for the other ones.
- Temporary traffic control is implemented in the heavy smog day, which aims to restrict the number of cars on the road. But EVs are always allowed to exempt the traffic control in those days.

3.2. The EV's adoption model

Through the classification of the results of previous researches, the factors that influence the purchase intention of EVs can be divided into two aspects: one is the characteristics of the population (or demographic characteristics), and the other is the attitude (or emotion) factor. As shown in Fig. 2, the demographic characteristics include gender, age, educational level, income level, marital status and geographical variables. The attitude factors include network externality, performance, price acceptability, government subsidies, usage cost, charging infrastructure, and concerns about smog.

The network externality reflects the impact of social influence on the purchase of EVs, while the performance parameters reflect the comparison of electric cars and traditional cars. Since consumers are often willing to pay more for the cost of EVs, so here the choice of price acceptance can reflect the influence of price factors. Government subsidies mainly refer to the satisfaction of government direct subsidies. The usage cost reflects the long-term usage expenditure of EVs compared with traditional cars. Charging infrastructure relates to the adequacy of the city's public charging infrastructure. As the most significant environmental concern for urban residents in China is smog, the concern about smog is chosen as a factor reflecting environmental behavior.

3.3. Survey design

A survey is designed and conducted to collect the empirical data about the purchasing intention of EV in China. The survey was implemented by a professional research company in August 2016. The primary data was obtained through a random survey conducted in China's four first-tier cities: Beijing, Shanghai, Guangzhou and Shenzhen. Though these four cities could not represent the whole China, we believe this study is still valuable for the understanding of EV purchasing intention in China. Firstly, these four sample cities with a population over 70 million, are the most developed regions in China. There are also a large number of areas around these cities, which have the similar cultural and economic development level such as: Yangtze River Delta and Pearl River Delta. The population of these areas exceeds 300 million. These areas are also the major markets of Vehicle. Secondly, the other regions are developing very fast and demonstrating the convergent to these sample cities. So the result of this paper may bring valuable information for other districts.

The questionnaire is designed with reference to the existing studies applied in other countries and takes into account the realities of China. When designing the questionnaires, we first determined the relevant factors that may impact the purchasing intention of electric vehicle through the literature research as mentioned in Section 2. Of course, these existing studies are most applied in other countries and the purpose of this paper is focusing on China market. So in the second process, a pre-survey was conducted from respondents in the field of China's energy research, and the suggestions for the problem setting were acquired. Considering the respondents' willingness to answer will drop with the increasing of the amount of questions, we finally decided to set one question for each factor.

The questions are divided into two parts. Part one examines demographic characteristics of the respondents, including the gender, income level, age, marital status, educational level, and whether they own a car. Part two focuses on the attitude factors that may influence

[1] For the high price vehicle like BYD E6, the subsidies proportion is only about 25%. But for the low price vehicle like Jianghuai iEV4, the proportion can reach 60%.

Table 2
EVs' subsidy policy of the central and some local government in China.

		100 km ≤ EV Range < 150 km	150 km ≤ EV Range < 250 km	EV Range ≥ 250 km	Other Policy
Central government subsidy (CNY[a])		25,000	45,000	55,000	Exempt purchase tax
Beijing	Local subsidy (CNY)	25,000	45,000	55,000	Exempts license lottery
	Total subsidy (CNY)	50,000	90,000	110,000	Exempts traffic control
Shanghai	Local subsidy (CNY)	10,000	30,000	30,000	Free license plates for green vehicles
	Total subsidy (CNY)	35,000	75,000	85,000	
Guangzhou	Local subsidy (CNY)	25,000	45,000	55,000	Exempts traffic control
	Total subsidy (CNY)	50,000	90,000	110,000	Exempts license lottery Exempts vehicle and vessel tax
Shenzhen	Local subsidy (CNY)	35,000	50,000	60,000	Higher license lottery Exempts toll charge
	Total subsidy (CNY)	60,000	95,000	115,000	Subsidy for charging infrastructure Electricity price favorable Parking fee favorable

[a] The unit CNY respect China Yuan, which is the monetary unit of China.

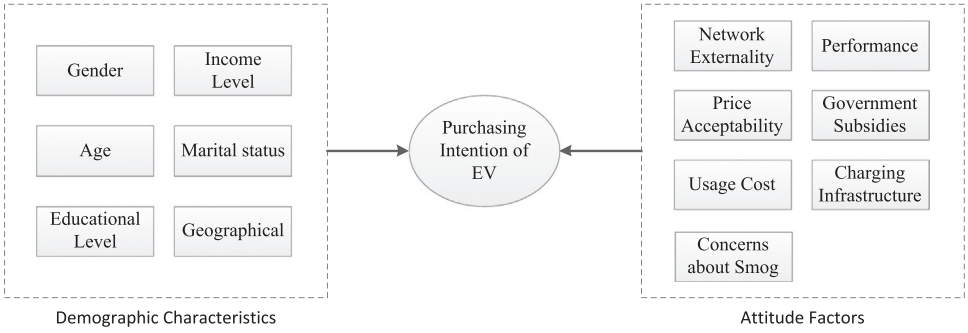

Fig. 2. The purchasing intention model of electric vehicle.

Table 3
The questions setting.

Factors	Questions
Network Externality (NE)	Are the people around you buying electric cars popular?
Performance (PE)	Do you think the performance (acceleration, driving comfort, etc.) of EV is better than traditional cars?
Price Acceptability (PA)	Do you think the price of electric cars is acceptable ?
Government Subsidies (GS)	Do you think the government subsidies for electric vehicles is sufficient ?
Usage Cost (UC)	Do you think the usage cost of electric vehicles compared to the traditional cars is competitive?
Charging Infrastructure (CI)	Do you think the public charging infrastructure of electric vehicles is sufficient ?
Concerns about Smog (CS)	Your level of concern about the urban smog problem ?
Purchasing Intention (PI)	Your willingness to buy an electric car ?

the purchasing intention of the EV. Table 3 lists the questions setting. The measurements are ranging from "1 to 5", where the 5 point means "Strongly Agree", and 1 point means "Strongly Disagree".

The method of questionnaire is often criticized due to the sample selection bias, and there is no perfect way to dispose this problem thoroughly. One common method is to do random sampling from the whole population being studied. We choose the mobile internet as the investigation method, which is conducted by the smartphone. The reason is that more than 74% of people in the first-tier cities use the smartphone to connect the internet (CINIC, 2017). Choosing the mobile internet makes the sample more representative.

4. Sample description

4.1. Demographic characteristics

A total of 1027 questionnaires were obtained. By setting identification mechanism, we exclude the invalid samples, and finally got 988 valid questionnaires. The method of identifying the invalid responses including: a) setting the same question in different positions of the questionnaire. If the responses to the question are different, we exclude the sample. b) Questioning which city the response is located. Due to the intent network could show the location of the mobile phone. If the location is inconsistent with the residential place, we will exclude the sample. Table 4 presents the detailed demographic attributes of the samples. Being similar to other studies, most of the respondents are male (63.4%), compare to female (36.6%). A majority of respondents' age (52.3%) are between the range from 26 to 35. We limit the minimum respondent age to 18 in the survey because that it's the legal age to drive in China. For the education level, the majority (46.5%) of the sample has a bachelor degree, followed by the junior college (22.4%). Personal monthly incomes of the sample are concentrated in "3001–5000" (30.4%) and "5001–8000" (31.8%), which represents a typical urban white-collar income levels. The married respondents (48.4%) are close to the single ones (51.6%). 44.9% of the respondents are car owners, which is close to half of the total sample. One may notice that most of the responders are under the age of 46. This is mainly because the young people have a higher intention to answer the questionnaire. To avoid the survivorship bias, we took the "age" as an explaining variable in the regression function.

4.2. Statistical description of the attitude factors

Table 5 presents the data description of the attitude factors and the

Table 4
Summary of demographic of the respondents.

Sample attributes		Observations	Percentage (%)
Gender	Female	362	36.6%
	Male	626	63.4%
Age	18 - 25	325	32.9%
	26 - 35	517	52.3%
	36 - 45	120	12.1%
	46 - 55	19	1.9%
	> 55	7	0.7%
Education Level	Junior middle school	66	6.7%
	High school	191	19.3%
	Junior college	221	22.4%
	Bachelor	459	46.5%
	Master and above	51	5.2%
Personal monthly income (CNY)	≤3000	124	12.6%
	3001–5000	300	30.4%
	5001–8000	314	31.8%
	8001–12000	167	16.9%
	12,001–20,000	67	6.8%
	≥20000	16	1.6%
Marital status	Married	478	48.4%
	Single	510	51.6%
Car owner	Owner	444	44.9%
	Not owner	544	55.1%
Location	Shanghai	218	22.1%
	Beijing	238	24.1%
	Guangzhou	272	27.5%
	Shenzhen	260	26.3%

normality testing for the data distribution. From the descriptive statistics of the factors, the mean values are around 3, and there is no extreme mean, which is consistent with the general questionnaire survey (people tend to choose the option near the median). The examination of normality is explored through Kolmogorov - Smirnov test, the result shows that the sample distribution conforms to the normal hypothesis.

Fig. 3 provides the detail of choice distribution. In the questionnaire, item 3 is a neutral option, and a score higher than 3 represent the responders who agree with that question. The mean values of network externality, performance and charging infrastructure are less than 3. The low mean value of network externality is mainly due to the fact that EV is relatively new products, and the proportion of people with EV is relatively low. For performance options, the value is close to 3, which shows that the current evaluation of the performance of EV is close to the traditional car. While the charging infrastructure scores are low, indicating that the charging infrastructure is generally considered inadequate.

The price acceptance has a mean score of 3.456; only 7.7% of the respondents think the price is unacceptable. More than 42.3% of the respondents think the current price of EVs is acceptable. 16.5% samples believe the government subsidies are insufficient, whilst by contrast, 33.2% holds the view that the intensity of subsidies is adequate. For the concerns about smog, the mean value has a higher score, reaching 3.89. More than 65.4% respondents agreed that urban smog is a serious problem. Especially, 56.2% agree they want to purchase EV, indicating that the public shows a strong willingness to purchase the EV.

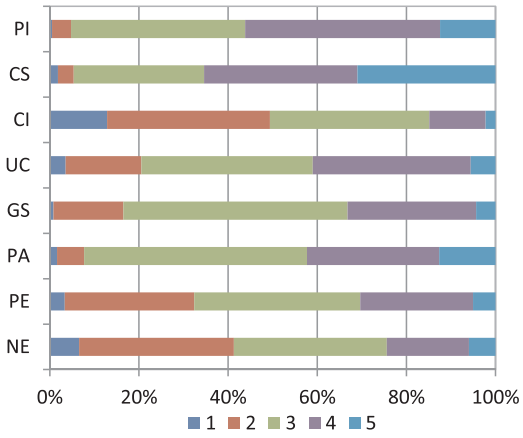

Fig. 3. The choice distribution of attitude factor.

As Green et al. (2014) pointed out, there may exist mainstream market bias. In our data, the public tends to think that the use of EVs cost more than traditional cars. But in fact, a large number of studies have concluded that, the usage cost of EVs may be lower (Peterson and Michalek, 2013; Wu et al., 2015; Karabasoglu and Michalek, 2013). And some studies have previously found that consumers lack the knowledge to calculate the payback of electric vehicle (Caperello and Kurani, 2012).

The Pearson correlation coefficient is a measure of the linear dependence between two variables. The Pearson correlation coefficient 'r' ranges from −1.00 to 1.00, where 'r = 1' indicates a perfect positive correlation, and 'r = −1' shows a perfect negative correlation. Table 6 presents the correlation matrix between the attitude variables. In general, the correlation coefficient when less than 0.2 could be considered as almost irrelevant. A correlation coefficient between 0.2 and 0.4 is considered low correlation; 0.40–0.70 is a moderate correlation and 0.70–0.90 is considered as high dependence. While the correlation coefficient of each variable in Table 6 is lower than 0.4, which indicates that the probability of multi-collinearity is low.

The matrix of Pearson correlation coefficient between the demographic factors is presented in Table 7. We can observe that the variable of monthly income correlated with nearly all other factors. Intuitively, the monthly income is often connected to education level, age and car ownership. This indicates that there may have collinearity between the demographic factors which should be disposed when conducting the regression function.

5. Results and discussion

Although some of the current studies are using multiple linear regression method to study the purchase intention of EVs, but as analyzed in the previous section, the distribution of variables is in line with the normal distribution. The logistic regression may be more appropriate

Table 5
Statistical description and reliability analysis.

Variable	Items	Mean	Standard Deviation	Skewness	Kurtosis	Kolmogorov-Smirnov statistics	KS Significance
NE	5	2.825	1.002	0.320	−0.432	0.208	0.000
PE	5	2.997	0.938	0.131	−0.555	0.195	0.000
PA	5	3.456	0.849	0.062	0.151	0.282	0.000
GS	5	3.202	0.782	0.075	−0.072	0.270	0.000
UC	5	3.225	0.916	−0.300	−0.245	0.211	0.000
CI	5	2.549	0.945	0.250	−0.286	0.213	0.000
CS	5	3.892	0.947	−0.550	−0.031	0.199	0.000
PI	5	3.634	0.773	−0.083	−0.041	0.244	0.000

Table 6
Correlation matrix between attitude factors.

	NE	PE	PA	GS	UC	CI	CS	PI
NE	1.000	0.386	0.212	0.225	0.108	0.424	−0.102	0.158
PE		1.000	0.138	0.146	0.196	0.282	−0.051	0.177
PA			1.000	0.232	0.027	0.250	0.140	0.292
GS				1.000	0.059	0.225	−0.035	0.168
UC					1.000	0.142	0.048	0.019
CI						1.000	−0.086	0.085
CS							1.000	0.257
PI								1.000

for the sample characteristics. Logistic regression is often used to model the association of a categorical outcome with independent variables for survey data (An, 2002). The logistic regression uses MLE rather than OLS. MLE allows more flexibility in the data because it has fewer restrictions, and many of the typical assumptions tested in statistical analysis could be avoided.

Therefore, this section uses ordered logistic regression to analyze the influence of demographic characteristics and attitude factors on the purchase intention of EVs. The dependent variable of the problem is the purchasing intention. Corresponding to Fig. 2, we select the demographic factors and attitude factors as independent variables. The effect of different factors on the purchasing intention can be determined. Table 8 presents the regression results of the three sets of models, and the details of the model are as follows:

Model 1 considers the demographic factors and attitude factors as the predictor variables. Gender and marital status are dummy variables with male gender variable being 1, female being 0; marital status variable being 1, unmarried being 0. Other demographic variables such as age, education level and income level, are assigned the value from 1 to 5 sequential. For example, if the age of the sample is located in the range of 18 − 25, the value of the variable is 1; and if the respondent is above 55 years old, the value of the age variable is 5. The LR statistic of model 1 is 206.141 with a high significance which indicates that the regression model fits the data well.

Model 2 excludes the monthly income, which may cause the collinearity problem as discussed in Section 4.2. The result shows that the variation of most coefficients is tiny. Though the coefficient of educational level has been changed, but the coefficient is still not significant.

Model 3 excludes the demographic variables, and only focuses on attitude factor variables. The coefficient values and significance of each variable in model 3 are similar to those of model 1, which indicates that, the collinearity between demographic factors and attitude factors is weak. The coefficients of network externality, performance, price acceptability, government subsidy and haze worry are higher, and they are significant. The LR statistic of model 2 is 191.266, with a high significance level.

According to the result of the regression models, we can recheck the impact of the factors as is shown in Fig. 2. Model 1 considers all the factors in Fig. 2 as predictors. The regression results of demographic variables show that, age has a significant and negative effect on purchase intention. This implies that consumer with a higher age may have a weaker purchase intention for EVs. This is mainly due to the fact that EV is relatively new products and the main consumer group is young people. Some studies have revealed that the older ones may have less intention to accept new products (Garling and Thogersen, 2001; Rogers, 2003). Marital status has a significant positive role in promoting. This may be due to the fact that after marriage, people will be more responsible and more willing to take action to protect the environment. Factors such as education level, income level and car ownership have no significant effect on the purchasing intention of EV. Among the attitude factors, the coefficient value and significance of “concerns about smog” are high. This is mainly due to the fact that the urban smog problem has a direct impact on all citizens. From Fig. 3, we can see more than 65.4% people are concerning about the smog. On the one hand, this indicates that the political basis of EV supporting policy is solid; on the other hand, the smog problem may be the major driving force of the adoption of EV.

The coefficient of price acceptance is also remarkable, indicating that the price of EV has a strong impact on the purchasing intention. While only 7.7% of responders think the price is unacceptable, meaning that the sales price of EVs has entered the scope that public could accept. This implies that though the EV market is still at a relatively preliminary stage of development, it already possesses the value of commercialization. The market scale may keep expanding with the further decline of price in the future.

In addition to price, the subsidies from the government for the purchase will also have a strong impact. As mentioned above, although both the price and government subsidies have a direct impact on the final expenditure of consumers, the mechanism of action may be different. The consumer may consider the subsidies as "revenue", and the subsidies may also allow the consumers with lower reservation price to purchase the EV.

The performance of EVs will also affect the purchasing intention significantly. However, the mean score of performance option is close to 3, indicating that the public believes that there is no obvious advantage compared with conventional fossil vehicle. The manufacturers need to spend more resources into R & D to enhance the performance advantages of EVs.

The network externality also has exerted in influence, and the coefficient is significant. The mean value of network externality is low. For one thing, this phenomenon reflects a truth that owner rate of EV is still low, so the network externality plays a smaller role. But for the other thing, we can draw an exciting conclusion that there exists a positive feedback mechanism in the number of EV. With the number of sales increases, the market demand will expand.

According to the regression results, the impact coefficients of usage cost and charging infrastructure are very small, and the coefficient is not significant. As Dumortier et al. (2015) and Caperello and Kurani (2012) figured out, consumers may lack knowledge to analyze the real usage costs. This may lead to a cognitive bias when answering the question. Axsen et al. (2017) also indicate that knowledge and understanding for EV are low across most participants.

For the charging infrastructure, home charging is the preferred option for EV users due to the cost advantage and convenience (Schroeder and Traber, 2012; Madina et al., 2016), so the public charging infrastructure may only have limited impact on the purchasing intentions. A survey conducted by Hou et al. (2013) also revealed that

Table 7
Correlation matrix between demographic factors.

	Gender	Age	Educational Level	Monthly Income	Marital Status	Car Owner
Gender	1.000	−0.001	0.035	0.174	−0.026	0.075
Age		1.000	0.005	0.318	0.530	0.212
Educational Level			1.000	0.407	0.049	0.143
Monthly Income				1.000	0.289	0.316
Marital Status					1.000	0.256
Car Owner						1.000

Table 8
Measure model result.

Variable	Model 1			Model 2			Model 3		
	Coefficient	z-Statistic	Prob.	Coefficient	z-Statistic	Prob.	Coefficient	z-Statistic	Prob.
Gender (Male = 1, Female = 0)	−0.246	−1.880	0.060	−0.216	−1.681	0.093			
Age	−0.281	−2.798	0.005	−0.255	−2.603	0.009			
Educational Level	0.010	0.145	0.885	0.045	0.723	0.470			
Monthly Income	0.079	1.210	0.226						
Marital Status (Married = 1, Single = 0)	0.375	2.475	0.013	0.399	2.654	0.008			
Car Owner (Owner = 1,Not Owner = 0)	−0.129	−0.951	0.341	−0.096	−0.723	0.469			
NE	0.195	2.634	0.008	0.198	2.671	0.008	0.192	2.603	0.009
PE	0.306	4.052	0.000	0.311	4.120	0.000	0.303	4.047	0.000
PA	0.553	6.651	0.000	0.555	6.671	0.000	0.558	6.769	0.000
GS	0.348	4.006	0.000	0.348	4.010	0.000	0.325	3.777	0.000
UC	−0.083	−1.155	0.248	−0.080	−1.119	0.263	−0.089	−1.247	0.213
CI	−0.116	−1.462	0.144	−0.120	−1.520	0.129	−0.121	−1.571	0.116
CS	0.548	7.567	0.000	0.540	7.501	0.000	0.549	7.704	0.000
LIMIT_2:C(14)	0.038	0.054	0.957	0.017	0.024	0.981	0.270	0.417	0.676
LIMIT_3:C(15)	2.415	4.293	0.000	2.397	4.267	0.000	2.631	5.288	0.000
LIMIT_4:C(16)	5.486	9.612	0.000	5.466	9.585	0.000	5.672	11.158	0.000
LIMIT_5:C(17)	8.031	13.293	0.000	8.008	13.271	0.000	8.192	15.013	0.000
Pseudo R-squared	0.091			0.090			0.084		
LR statistic	206.141			204.674			191.266		
Prob (LR statistic)	0.000			0.000			0.000		
Akaike info criterion	2.124			2.124			2.127		
Log likelihood	−1032.423			−1033.156			−1039.861		

most of the travel distance in city is short distance, and the self-charging is sufficient for the daily travel demand.

According to the result, we can refer back to Fig. 2 and make an overview to show which parts of the figures stood out from our findings. Firstly, we can find what factors may have significant impact on the purchasing intention. These factors including gender, age, marital status, network externality (NE), performance (PE), price acceptability (PA), government subsidies (GS) and concerns about smog (CS). These factors are important and could be used to improvement the current policy. Secondly, the impact could be quantified. The PA and CS are the most prominent factors that may impact the intention of purchase. Thirdly, by comparing different model, we can see that the influence of demographic factors and attitude factors is independently, which means their transmission mechanisms are different.

6. Policy implications

The results of this paper bring us a prospect about how the consumer's attitude factors could influence the purchasing intention of EV. Some of our findings could provide valuable information for the policy makers and industry. The main policy recommendations of this paper are listed as follows:

Concerns of smog are now a powerful motivation for the urban residents to adopt EVs. For the cities which have a serious air condition, the purchasing intentions of EV may be higher than others. To promote the application of EVs, the government could offer discrepant subsidies for different regions, which may allocate more resources for the most polluted cities. Meanwhile, the manufacturers of EV should also consider these cities as the key area of their main market penetration targets.

From the results of the survey, we can know that the price of EVs has currently fallen into the range that can be accepted by the public. The price acceptance is also an important factor that may influence the intention of purchasing EVs. This can draw an exciting conclusion that the EV has the ability to survive in the market competition. Whereas, for the consumer, the price with subsidies is the expenditure cost for vehicle. If the subsidies are decreasing in the future, the demand for EV may also decline. Subsidies may be essential if the government wants to accelerate the penetration rate of EV.

Although the China's government provides enormous subsidies for EVs, the public still doesn't think the subsidies are sufficient. The development of EV is an important method to solve the smog problem in the urban area. Government subsidies have a significant and positive impact on the purchasing intention. Some may argue that the subsidies may waste the public finance and cause market distortion. But considering the positive externalities of the EV, such subsidies may be worth if the government wants to address the air pollution problem.

Network externality has a positive impact on the purchasing intention of EVs. However, the current amount of EV is relatively small, and the role of network externality in promoting the adoption of EVs is limited. There will be positive feedback effect that the demand of EV may increase with the growth of the EV's share in vehicle market. The government can design appropriate policy, such as EV license plate and EV priority in heavy traffic periods, to increase the exposure of EVs and amplify the impact of network effect.

Performance has a significant impact on the public's willingness to buy the EVs. However, the public's evaluation about the performance of EVs is neutral, which means that people don't think the EV's performance outperforms the gasoline vehicle. In addition, contrary to the intuitions, the usage cost of EVs has little influence on consumers' purchasing intention, and the influence is not significant. The public's evaluation about the cost of EV is close to that of the conventional gasoline vehicle. In reality, the EV has some unique advantages such as a better accelerate performance, and the EV has obvious cost advantage in the usage process comparing with the conventional vehicle, because that the cost of electricity is lower than gasoline, due to the heavy tax of fossil fuel in China. The phenomenon that public undervaluation the performance of EV may be that most people do not have the experience of using EVs, so they don't know the actual performance. As many previous researched pointed out, the consumer may also lack knowledge to calculate the real usage cost. These results imply that the manufacturer should enhance their sale strategy which provides more test driving vehicles and improve the specialized knowledge of the sales. The government could reinforce the public awareness in according to the method like noncommercial advertising. In addition, the market intermediaries, like sales and sales and dealerships, may play an important role for the promotion of EVs. Matthews et al. (2017) pointed out that the lacking of availability of vehicles on site is a common barrier for customers to adopt EV, and even the sales always transmit the inaccurate information for the customers. The current distribution

channel of EV in China is still the traditional method; that is there still need enormous salesmen and dealerships to serve clients face to face. The vehicle buyer is also need 3–6 months waiting for their vehicle, and the price of the vehicle will increase because of the sale cost. The EV manufacturer of China should enhance their distribution channel. Tesla has made a great demonstration, which provides a sample of a car in a showroom but then fulfills the customers' orders.

Being different from some previous researches, this paper finds that the coverage of charging infrastructures has limit impact on willingness to buy the EV. The main reason for this phenomenon may be that most of the daily travel in the city is short-range usage, and the home charging can satisfy most of the daily requirement for the public. This finding provides more information for the government to adjust the policy. At present, the government plans to construct more charging stations to stimulate the usage of EVs. Some private underground garages are not allowed to install small power battery charger due to the limitation of power supply capacity in residential areas and other regulation. Therefore, priority policies should be focus on expanding the grid infrastructure to guarantee the power capacity of home charging system.

Group differences also lead to different purchasing intentions. From our result, the groups such as female, younger and married people have a higher intention to buy the EV. This implies that diversified policies can be made to enhance the efficiency of subsidies, and more accurately products could be launched to meet different types of consumers' demand. For example, females are more willing to accept electric cars, so the manufactures could give a priority to the vehicle type which is preferred by female in the designing step. In addition, the EV is more accepted in the young group and marital group, which means that the government can design targeted subsidies for these groups, such as offering a prime rate of vehicle loan for the first-time buyer and family cars.

7. Conclusions

This paper analyses the main factors that may affect the purchasing intention of electric vehicles based on the survey data in four of China's most largest and developed cities: Beijing, Shanghai, Guangzhou and Shenzhen. When designing the survey questionnaire, we refer to the experience of the previous literature, and take into account the realistic situation of China. Both the demographic factors and the attitude factors have been examined. For the demographic factors, we examine the variables including gender, age, education level, income level, marital status and vehicle owner. The attitude factors, such as network externality, performance, price acceptance, government subsidies, usage cost, charging infrastructure and concerns about smog, are also analyzed

A logistic regression is applied to identify the influence of these factors. The result demonstrates that the most important elements affecting the purchase intention are the concerns about smog and price acceptance. In addition, factors such as government subsidies, performance and network externality, gender, age and marital status also play an important role in the EV purchasing intention. Such findings enhance our understanding on consumer preferences and public's acceptance toward the new vehicle technology.

The results of this study partially verify the conclusion of previous research. Meanwhile, some different findings in China's market are also proposed. These conclusions of this study have proposed a series of useful information for policy makers and stakeholders.

Based on the conclusions of this paper, a series of interesting problems can be proposed for further studies. Firstly, the analysis of external factors in this paper only examines whether the external factors will have an impact on the purchase willingness. Future research could focus on more accurate analysis such as demand price elasticity, demand subsidy elasticity etc. Secondly, this paper only roughly analyses the differences among population groups, the deeper relationship would be examined by applying other technology methods such as cluster analysis. Besides, the causal relationship between factors is still unknown in the paper; a structural equation model should be founded for further studies.

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