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Effects of providing total cost of ownership information on below-40 young consumers' intent to purchase an electric vehicle: A case study in China

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ABSTRACT

Compared to gasoline vehicles, electric vehicles have an advantage that financial benefits from reduced energy consumption offset much or all of the initial price premium. However, currently there exists consumer misconception of this advantage. One strategy to address this misconception is to provide life cycle cost information to consumers. This study investigates how providing information about 5-year fuel cost and total cost of ownership affects the stated preferences of 'below 40' young consumers for a gasoline, plug-in hybrid, or battery electric vehicle in the context of China. A rank-ordered logit model is developed to model consumers' stated preferences, based on data collected through a stated preference experiment. This study evidenced the significant positive effect of providing 5-year fuel cost and total cost of ownership information on the stated preference for electric vehicle. Socioeconomic attributes such as gender and education level are also found to have effects on consumers' electric vehicle purchasing intent. The results enhance the understanding of consumers' complex electric vehicle purchase decisions and have policy implications for electric vehicle promotion.

1. Introduction

High dependency of the automotive industry on the unrecyclable and limited fossil resources, and rapidly increasing environmental pollution, are big challenges for the sustainability of humans and the planet (Hartig and Kahn, 2016; O'Brien, 2015). Electric vehicle (EV), an alternative of conventional gasoline vehicle, is a promising solution to the above challenges. Many countries have taken various measures to encourage consumers to purchase electric vehicles. For example, California promotes electric vehicles through policies such as the Zero Emission Vehicle Program (ZEVP) and the Clean Vehicle Rebate Project (CVRP). Specifically, the Zero Emission Vehicle Program promotes zero-emission vehicles through a combination of forcing automakers to sell a certain percentage of zero-emission vehicles and allowing credit trading, and the Clean Vehicle Rebate Project provides a flat-rate subsidy for electric vehicles according to vehicle type, focusing on fairness and setting differentiated subsidy amounts for different income groups and consumption purposes. The global auto market has witnessed a rapid growth in electric vehicle productions and sales during the past ten years, though the current market share of electric vehicle is still small (IEA, 2019). In China, the government is very active in promoting electric vehicle. Battery electric vehicle (BEV) and plug-in hybrid electric vehicle (PHEV) are two types of electric vehicles that China supports, as dictated by Chinese government's 'The Energy Conservation and New Energy Vehicle Industry Development Plan (2012–2020)' (China State Council, 2012). Now China has been the world's biggest electric vehicles market (Tu and Yang, 2019).

From the demand (i.e., consumer) side, however, many car consumers seem not to be as interested in electric vehicle as government has expected. They may decline to purchase electric vehicles which have lower operating cost and will potentially be net-cost savers in the long-term (Al-Alawi and Bradley, 2013; Dumortier et al., 2015; Ji et al., 2021). For many car buyers, there exists a lack of an intuitive understanding for the relative prices of gasoline and electricity. Also, the different amounts of gasoline and electricity that are used by a car over the lifetime are usually unknown or unclear to car buyers (Dumortier et al., 2015). This is evidenced by interviews with consumers in Chinese big cities such as Shanghai where citizens' awareness of electric vehicle is high and the electric vehicles market share is much bigger than the nation's average level (Gan and Liu, 2018). Moreover, the continual

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decrease in state and local government subsidies for electric vehicles in some countries is undoubtedly unfavorable for consumers' electric vehicle purchase.

Given the above context, it is critical and interesting to investigate the impacts of providing life cycle cost information (e.g., 5-year fuel cost and total cost of ownership) on people's intent to purchase an electric vehicle. Our literature review (presented in the remaining part of this section) shows that, the effect of providing total cost of ownership (TCO) information on electric vehicle purchasing intent has been rarely reported, although numerous empirical studies have addressed electric vehicle purchasing decisions and have identified many important factors influencing electric vehicle purchasing intent.

Socioeconomic characteristics such as gender, income and education level have been shown to correlate with consumers' propensity to purchase electric vehicles (Li et al., 2013; Lin and Tan, 2017; Tal et al., 2013; Tian et al., 2021). Men with high education and high mileage are less likely to purchase a hybrid electric vehicle (HEV) (Li et al., 2013). Women with higher incomes generally show a higher willingness to purchase new energy vehicles (Tian et al., 2021). A revealed preference survey from California, USA, also finds that households with electric cars are more affluent (Tal et al., 2013). Through a survey of four developed cities in China, Lin and Tan (2017) find that people with higher incomes and education are more likely to buy battery electric vehicles.

In addition to socioeconomic factors, price, prior personal experience with electric vehicles and environmental awareness are also potentially important factors influencing an individual's intent to purchase an electric vehicle. Consumers are price sensitive, and the high price of electric vehicle is a significant barrier to purchase (Shalender and Sharma, 2020). Behavioral intent to purchase an electric vehicle increases when consumers have prior personal experience with electric vehicles (Kim et al., 2019; Larson et al., 2014; Schmalfuβ et al., 2017). When consumers are more environmentally conscious, their electric vehicle purchasing intent increases (Axsen et al., 2015; de Luca et al., 2020; Degirmenci and Breitner, 2017; Jiang, 2016; Lane et al., 2018; Tu and Yang, 2019; Verma et al., 2020).

Studies have shown that financial incentives expand the market for electric vehicles (Gallagher and Muehlegger, 2011; Hardman, 2019; Münzel et al., 2019; Ou et al., 2019; Qian et al., 2019; Wu et al., 2021). Furthermore, many studies have compared the cost-effectiveness and impact of different policy designs to further evaluate policy effectiveness (Deshazo et al., 2017; Gregory et al., 2021; Sheldon and Dua, 2019 & 2020). Deshazo et al. (2017) develop a series of experiments for California's plug-in electric vehicle rebate program to simulate and evaluate performance metrics (total cost effectiveness, additional electric vehicles sold, etc.) and consumer heterogeneity under various alternative rebate policy designs. The experimental results show that rebate programs under different strategies have different impacts on plug-in electric vehicle sales and that policymakers can induce more plug-in electric vehicle sales by redesigning plug-in electric vehicle rebate programs. Gregory et al. (2021) find that for low-moderate income households in California, vehicle financing policies are more cost-effective than subsidies and more likely to increase adoption of clean vehicles. Sheldon and Dua (2019) analyze the effectiveness of California's "Replace Your Ride". The program provides targeted subsidies to low-income households living in local areas with poor air quality to replace older vehicles with cleaner vehicles. As it turned out, the policy is successful in boosting additional electric vehicle sales in 2015. Subsequently, Sheldon and Dua (2020) explore the impact of two measures on China's plug-in electric vehicle market share under a subsidy halving scenario, one without any countervailing measures and one with zero subsidy for high-income consumers and a higher subsidy for low-income consumers. The results show that the latter has a 13% less decline in plug-in electric vehicle market share than the former. Two revealed preference surveys from China also confirm the effect of the new energy vehicle promotion policy on consumers (Wang et al., 2021; Xiong et al., 2019).

Other factors have been shown to be associated with the purchase of electric vehicles. For example, the willingness to purchase an electric vehicle is higher among consumers who already know somebody with an electric vehicle (Habich-Sobiegalla et al., 2018) and electricity prices are negatively associated with electric vehicle use (Soltani-Sobh et al., 2017). Environmental stimuli (e.g., economy, promotions, and air quality) and psychological factors also have an impact on consumers' purchase behavior of electric vehicle (Li et al., 2021).

The influence of information provision on consumer behavior is a heated topic in disciplines such as marketing, management science, and environment economics (Cawley et al., 2020). Several domestic and international studies have demonstrated that information (e.g., calorie information on menu labels, nutritional information on food labels, and poverty alleviation labels, etc.) provision does influence consumers' choice intention (Agnes and Klaus, 2018; Bandara et al., 2016; Cawley et al., 2020; Gong and Zhou, 2020; Li and Zheng, 2021; Liu et al., 2018; Maaya et al., 2020). Palmer et al. (2018) argue that the lack of reliable information on the total cost of ownership of electric vehicle is an additional barrier to purchase. By comparing the total cost of ownership of plug-in hybrid electric vehicle and battery electric vehicle in three countries, the UK, the US and Japan, they find a clear link between the total cost of ownership of plug-in hybrid electric vehicle and market share. Total cost of ownership is a measure of purchase price, fuel cost, and other costs over the ownership period (Dumortier et al., 2015). Research suggests that car buyers who are more fuel economy conscious may prefer electric vehicles (Hamamoto, 2019). Interestingly, the experiment finds a rebound effect from the purchase of electric vehicles, meaning that the purchase of hybrid electric vehicles leads to an increase in annual miles driven per household, which could lead to an increase in CO_2 emissions.

Some recent studies about total cost of ownership in the energy discipline finds that hybrid electric vehicle and battery electric vehicle are more cost-effective than conventional gasoline vehicle (CV) (Al-Alawi and Bradley, 2013; Hagman et al., 2016; Sharma et al., 2012, 2013). To understand the costs and benefits of plug-in hybrid electric vehicle purchase and use, Al-Alawi and Bradley (2013) construct a total cost of ownership model for hybrid vehicles in the US. The model is then used to compare and conduct sensitivity analyses of different plug-in hybrid electric vehicle designs for four models. The results indicate that the more comprehensive plug-in hybrid electric vehicle ownership cost model has a lower net cost of ownership, which leads to higher consumer preferences. A Swedish study constructs a consumer-centric total cost of ownership model to compare the differences between the purchase price and total cost of ownership of sample vehicles (Hagman et al., 2016). The experimental results show that in Sweden, the total cost of ownership of a battery electric vehicle is more competitive compared to an internal combustion engine vehicle (ICEV) and a hybrid electric vehicle, which helps to attract more consumers to purchase battery electric vehicles. By comparing the cost differences between battery electric vehicle, internal combustion engine vehicle and hybrid electric vehicle, it is found that the battery cost is an important reason for the high purchase price of battery electric vehicles, and it is expected that the battery cost will decrease in the future with the development of technology, which will lead to the purchase price and total cost of ownership are more competitive. Sharma et al. (2012&2013) conduct two studies in Australia on plug-in hybrid electric vehicles, battery electric vehicles, and conventional gasoline vehicles whose two vehicle sizes, Class-E and Class-B, are considered: 1) The first study measured the economic effects of the three vehicles by calculating the total cost of ownership of the three vehicles that could take into account changes in fuel, electricity, and battery prices. 2) The second study measures the greenhouse effect of the three vehicles by calculating the life cycle greenhouse gas emissions. Combining the total cost of ownership from the first study, the cost of reducing life cycle greenhouse gas emissions through electrification of passenger transport can be estimated for different scenarios. The experimental results show that the Class-E electric vehicle is more economically efficient and emits less greenhouse gases.

Dumortier et al. (2015), through developing a discrete choice model based on the data collected from a stated preference experiment in the US, find that, providing life cycle cost information (i.e., 5-year fuel cost savings and total cost of ownership shown on a car information label) increases the probability of respondents' electric vehicle choice. Their work has policy insights for electric vehicle promoting and behavioral interventions. They find that providing 5-year fuel cost savings information has little impact on consumers, although this information has been implemented on the car information label. Total cost of ownership information has not been included on car information label, but providing it leads to higher rankings of small and medium-sized vehicle enthusiasts choosing electric vehicles. Therefore, they suggest more explorations of the impact of providing life cycle cost information on consumer behavior are necessary to determine whether such information should be added to a car information label.

Internationally, many empirical studies have shown that age is significantly related to the electric vehicle purchasing intent and young consumers below 40 or 45 years of age are more likely to buy or are major consumers of electric vehicles (Hidrue et al., 2011; Huang and Gu, 2021; Junquera et al., 2016; Potoglou and Kanaroglou, 2007; Wang et al., 2015; Ziegler, 2012). A Canadian survey on factors influencing household choice of clean cars reveals a preference for clean cars among respondents under the age of 45 (Potoglou and Kanaroglou, 2007). An American study of stated preferences for electric vehicle choice demonstrates that younger or more middle-aged respondents are more likely to accept electric vehicles than older ones (Hidrue et al., 2011). Both the Spanish and German studies find that younger people are more likely to buy electric vehicles, and these studies suggest electric vehicles manufacturers and advertising campaigns should focus on appealing to younger people (Junquera et al., 2016; Ziegler, 2012). In addition to the above stated preference surveys, a number of large-scale revealed preference surveys from the United States have found that, all else being equal, the probability of purchasing an electric vehicle decreases with buyer age and increases with income (Dua and White, 2020; Dua et al., 2019; Xing et al., 2021). Similar findings have been found in China. Wang et al. (2015) find that age has a significant effect on the market acceptance of electric vehicles, with a higher percentage of respondents in the 31–40 age group being more willing to purchase an electric vehicle to replace a fuel vehicle than other age choices. Huang and Gu (2021) also find that respondents below 40 years of age are more willing to purchase an electric vehicle. However, few studies that investigate the effect of providing total cost of ownership information on the purchasing intent target the 'below 40 or 45 young consumer' sub-population.

The above review indicates the current scarcity of research about the effect of providing total cost of ownership information on the purchasing intent of the 'below 40 or 45 young consumer' sub-population who account for the majority of the electric vehicle buyers. To fill this gap, this paper addresses the effects of providing total cost of ownership information on young consumers' (18–40 years old) intent to buy electric vehicles in the context of China. More specifically, it investigates the effects of providing 5-year fuel cost and total cost of ownership information on Chinese 'below 40 young consumers' electric vehicle purchasing intent, through developing an econometric model based on data collected from a stated preference (SP) survey. The study of this paper enriches the understanding of the complex electric vehicle choice behavior and has useful insights for the promotion of electric vehicles in China.

The rest of this paper is organized as follows. First, the stated preference experiment that collects behavioral data is presented. Then, an econometric approach (i.e., a rank-ordered logit) to modeling electric vehicle purchasing intent is depicted, followed by model results and discussions. Last, concluding remarks are given.

2. Data collection

2.1. Experimental design

The huge majority of vehicles that Chinese families own are small or medium-sized cars, and only PHEV and BEV are two EV types that Chinese government support in the time of this study (China State Council, 2012). Thus, this study addressed three types of small/medium sized cars: 'CV', 'BEV', and 'PHEV'.

This study used 'generic' cars in the SP experiment, so as to avoid the possible influence on a respondent of preference for or loyalty to a particular car brand or model. Generic cars have been commonly used in EV engineering-economic analysis (e.g., Al-Alawi and Bradley, 2013; Dumortier et al., 2015). In this study, the three generic cars (i.e., three options) are comparable and competitive, and have prototypes in the real market.

This study, based on data collected from the 'DiYiDianDong' EV website (www.d1ev.com), considered the top fourteen best sale EVs whose sales in 2016 accounts for nearly half of the whole EV market sales. From the fourteen EVs, this study chose the '*BYD-Qin*' PHEV and the '*BYD-EV*' BEV as the prototypes of the generic EV cars. '*BYD-Qin*' and '*BYD-EV*' have very close size and performance characteristics except the propulsion system and drive train. On the other hand, this study considered the top twenty best sale CVs based on the 2016 data collected from a popular car sales website (www.qichenu.com) in China. From the twenty CVs, this study chose '*Buick-VERANO* (1.5 T)' as the prototype of the generic CV because it is the closest car to the two prototype EVs in terms of performance characteristics.

Given the three generic cars, their '5-year fuel cost' and '5-year total cost of ownership (TCO)' can be calculated. The vehicle kilometers traveled (VKT) is assumed to be 12,000 km/year on average, and energy consumption is assumed to be 6.1 L/100 km, 1.6 L/100 km, and 13.5 kW h/100 km for CV, PHEV, and BEV respectively, which reflects real situations in typical Chinese cities (Beijing Transport Institute, 2019). $0.9316/L and $0.0096/kW•h are used for fuel and electricity prices respectively, and a 5-year lifetime is used for life cycle cost considering Chinese real situations (Ji et al., 2021). By calculation, the 5-year fuel cost for CV, PHEV, and BEV is $3,434, $896, and $836 respectively. The actual purchase price is calculated after considering the initial purchase price, sales tax exemptions (applicable to EVs) and government subsidies (applicable to EVs). The actual purchase price of CV, PHEV, and BEV is $25,978, $26,277, and $17,040 respectively.

Based on the existing studies (Al-Alawi and Bradley, 2013; Dumortier et al., 2015) and the actual situation in China, the metric TCO in this study consists of three components: acquisition cost, usage cost and residual value (TCO = acquisition cost + usage cost - residual value). The acquisition cost is mainly composed of vehicle selling price, vehicle purchase tax and tax subsidies, of which consumers who buy vehicles with 1.6L displacement and below need to pay 7.5% purchase tax, while consumers who buy new energy vehicles not only do not need to pay purchase tax but also receive additional subsidies (Ministry of Finance, State Administration of Taxation of China, 2016). The usage cost refers to the cost of keeping and using the car, which includes fuel consumption, insurance, repair and maintenance, over-the-road parking, taxes and other expenses that grow cumulatively over time. A residual value rate of 5% and a service life of 15 years are used to calculate the residual value of the three types of cars after 5 years of use (Gan and Liu, 2018). The final TCO obtained for CV, PHEV, and BEV is $20,810, $18,548, and $17,040 respectively.

In the Chinese auto market, fuel economy information is not available to consumers when they buy new cars from a dealer. Unlike some developed countries such as USA, Chinese government does not require vehicle manufactures to include fuel economy information. Moreover, a car dealer's car information label and promotional materials do not include fuel economy information.

Given the above context, this study designs three stated choice scenarios in which the hypothetical car information label varies in level of detail for life cycle cost information. The three choice scenarios are: (1) Scenario1 (*'basic car information'*). In this scenario, respondents are presented a car information label that displays basic car information which includes engine capacity, range, maximum speed, government subsidy, sales tax, fuel price, fuel consumption per 100 km, and actual purchase price. (2) Scenario 2 (*'basic car information'* + *'5-year fuel cost information'*). In this scenario, respondents are presented a car information label that displays both basic car information and 5-year fuel cost information. (3) Scenario 3 (*'basic car information'* + *'5-year fuel cost information'* + *'5-year TCO information'*). In this scenario, respondents are presented a car information label that displays basic car information, 5-year fuel cost information, and 5-year TCO information. Appendix A gives the above three choice scenarios.

2.2. Survey

The SP experiment was conducted in the form of an online questionnaire survey. The questionnaire contains two parts. The first part is the question that asks respondents to state their ranking of three new car options (i.e., 'CV', 'PHEV', and 'BEV') under a certain stated choice scenario. The second part includes some questions about a respondent's socioeconomic characteristics such as gender, income and education level. In the survey, respondents were asked to pick their most preferred vehicle and pick their least preferred vehicle. This is equivalent to ask a respondent to rank the three car types (Train, 2009).

Fig. 1 presents the car information label designed for Scenario 3 and the associated choice question in the SP experiment. The figure was adapted from its original Chinese version. Fig. 2 gives a schematic illustration of key elements of Scenarios 1, 2, 3, highlighting their differences and relationships.

Since many Chinese cities have already had a huge coverage of public charging stations which avoid charging stations availability concerns among potential EV buyers, the respondents were asked to assume that they can easily find a public charging station in a city they live.

The linkage to the survey website was sent to citizens in the Jinan City, Shandong Province, China, via popular Chinese social networking apps Wechat and QQ. The survey was conducted in May 2020 among all people under 40 years old, and a total of 166 respondents submitted questionnaires. After removing 3 invalid questionnaires in which a respondent did not answer all the questions, this study finally obtained

There are three types of commercially available cars A,B, C, and the basic information and prices of the three types of cars are known as shown below.

Conventional Vehicle (Option A)

Engine capacity: 1.5T
Range: >= 450km
Maximum speed: 205km/h
Subsidy: none
Sales tax: 7.5%
Fuel consumption: 6.1L/100km

Actual purchase price: $25,978
Fuel cost: $3,434 (5years)
Total cost of owner: $20,810 (5years)

Plug-in Hybrid Electric Vehicle (Option B)

Engine capacity: 1.5T
Range: >= 450km
Maximum speed: 185km/h
Subsidy: $5,076
Sales tax: none
Fuel consumption: 1.6L/100km
(Pure electric model: 13.5kW •h/km; Pure fuel model: 6.1L/100km)

Actual purchase price: $26,277
Fuel cost: $896(5years)
Total cost of owner: $18,548 (5years)

Battery Electric Vehicle (Option C)

Range: >= 300km
Maximum speed: 185km/h
Power consumption: 13.5kW•h/km
Subsidy: $11,048
Sales tax: none

Actual purchase price: $24,037
Fuel cost: $836 (5years)
Total cost of owner: $17,040 (5years)

Please choose		**A**	**B**	**C**
	(1) the car you are most willing to buy:	○	○	○
	(2) the car you are least likely to buy:	○	○	○

Fig. 1. Car information label for Scenario 3 in the SP experiment.

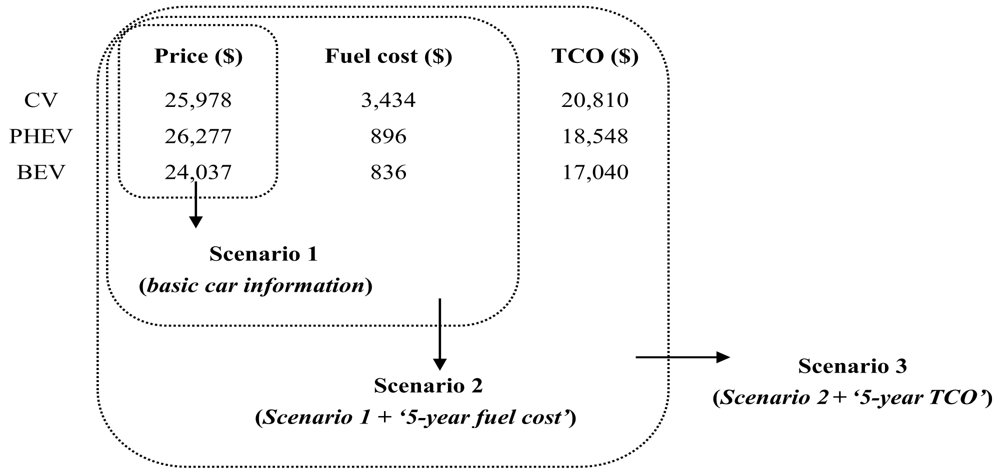

Fig. 2. Relationships among key elements of three Scenarios.

163 valid questionnaires (i.e., 489 choice samples) for model development.

2.3. Sample characteristics

Table 1 presents descriptive statistics. In the sample, nearly two third of the respondents are female. The huge majority (95%) of the sample have a college or higher degree. About 30% of respondents have no cars in their family, while 57% of the respondents have only one car and the rest have 2 or more cars. For the majority (about 80%) of the respondents, the commuting distance is less than 10 km. Nearly 30% of respondents have a desired purchase price below $15,000 and about 60% of respondents have a desired purchase price between $15,000 and $30,000, the rest respondents desired purchase price exceeds $30,000.

2.4. Analysis

Table 2 and Fig. 3 present choice patterns of the three vehicle types chosen as the most preferred vehicle by respondents. First, as Fig. 3 shows, with the increase in level of detail for life cycle cost information provided by the car information label, the choice percentage for BEV as the most preferred vehicle rises. Second, the choice percentage for PHEV as the most preferred vehicle increases when 5-year fuel cost information is provided to respondents (i.e., from Scenario 1 to Scenario 2), while the additional information of 5-year TCO provided (from Scenario 2 to Scenario 3) leads to a choice percentage drop to a level lower than that in Scenario 1. Third, providing life cycle cost information (Scenario 2 and Scenario 3) leads to an obvious choice percentage drop for CV, though increasing level of detail for life cycle cost information (from Scenario 2 to Scenario 3) brings a very slight and negligible increase in choice percentage (i.e., 0.6%), as Table 2 shows.

Table 1
Descriptive statistics.

Attribute	Percentage
Gender	Male: 36%; Female: 64%.
Education level (Education)	Secondary Schools: 5%; Undergraduate: 64%; Graduate students: 31%.
Car ownership (Numbercar)	0: 31%; 1: 57%; ≥2: 12%.
Commuting distance (Distance)	<5 km: 56%; 5–10 km: 22%; >10 km: 22%.
Desired car purchase price (Desired price)	<$15,000: 31%; $15,000-$30,000: 58%; >$30,000: 11%.

Note: variable names are in parentheses, consistent with those in Table 3.

The following sections will quantitatively analyze the above SP data through developing an econometric model.

3. Model development

This study adopted the rank-ordered logit model to analyze the collected SP data, since the SP experiment collected ranking data about respondents' stated preference. The merit of a rank-ordered logit as compared to the conventional multinomial logit is that the rank-ordered logit makes full use of the information contained in the ordinal ranking of all options in the choice set to estimate the model parameters (Train, 2009). In this study, the ordinal ranking is among the three competitive vehicle types.

The random utility framework is usually used to derive the rank-ordered logit model (Train, 2009). It assumes that there are J alternatives and N individuals. For individual i, the utility of alternative j is given by U_{ij}, where $i = 1, 2, \ldots, N$, $j = 1, 2, \ldots, J$. It is assumed that an analyst (modeler) does not directly observe U_{ij}. Instead, the analyst constructs a random utility model of the form $U_{ij} = V_{ij} + \varepsilon_{ij}$ where V_{ij} is the deterministic component of the utility that is observed by the analyst and the disturbance term ε_{ij} is a random component and is independent and identically distributed (IID) extreme value. The specification of V_{ij} usually takes a linear-in-parameter functional form which can be written as $V_{ij} = \beta X$. In this specification, β is a vector of coefficients and X are the explanatory variables.

The alternatives are the three cars, i.e., $J = 3$ and the probability that alternative j is picked by individual i increases in V_{ij}. Let r_i be a vector whose elements r_{ij} represent the ranking of alternative j by respondent i, i.e., $r_i = \{r_{i1}, \ldots, r_{ij}, \ldots, r_{iJ}\}$. For simplicity of exposition, let us suppose the order of the options in the choice set is just the order of the rankings of the options. Then the probability that the analyst observes this particular ranking is written as

$$P(r_i|\beta) = P(U_{ir_{i1}} > \ldots > V_{ir_{iJ}}) = \prod_{j=1}^{J-1} \frac{\exp\left(V_{ir_{ij}}\right)}{\sum_{l=j}^{J} \exp\left(V_{ir_{ij}}\right)}$$

The multinomial logit (MNL) and the rank-ordered logit have some similarities. The rank-ordered logit can be thought of a sequence MNL model in which the pool of alternatives diminishes with each alternative receiving a ranking (Train, 2009).

In this study, the open-source R language (v.3.6.3; R Development Core Team, 2020) is used to estimate the rank-ordered logit model.

Table 2
Summary of choices for the most preferred vehicle.

Category	Scenario 1		Scenario 2		Scenario 3	
	Frequency	Percentage	Frequency	Percentage	Frequency	Percentage
CV	41	25.1%	30	18.4%	31	19.0%
PHEV	94	**57.7%**	98	**60.1%**	88	**54.0%**
BEV	28	17.2%	35	21.5%	44	27.0%

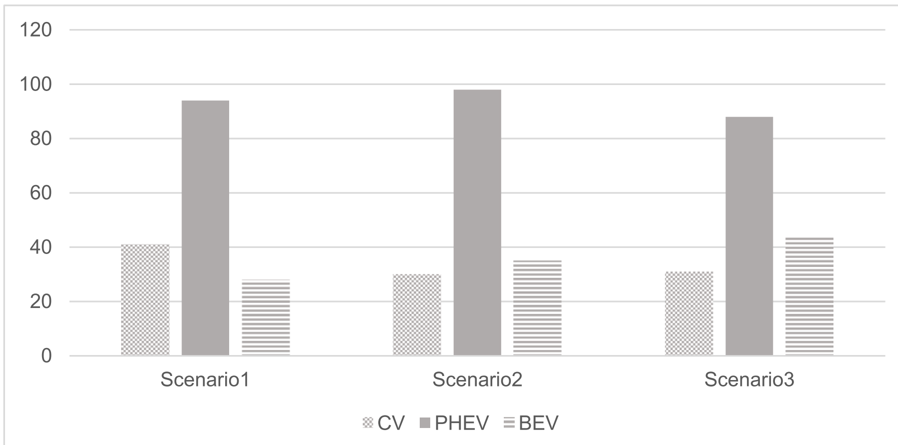

Fig. 3. Percentage choices for the most preferred vehicles in each scenario.

4. Results and discussions

4.1. Results

The model estimation results for the rank-ordered logit model are presented in Table 3. The CV is chosen as the reference option. Variables contained in the model specification include scenario dummies, gender, education level, car ownership, commuting distance, and desired car purchase price. Those explanatory variables obtaining a significant coefficient (significance at the 10% level) have figures in bold type for columns 'Coefficient' and 'z-value'.

The rank-ordered logit model fits the SP data collected in this study well, with the McFadden R^2 being about 0.3. This shows the appropriateness of the rank-ordered logit model being chosen in this study.

4.2. Discussions

First, as shown in Table 3, providing additional 5-year fuel cost information (Scenario 2) will increase the probability of a respondent's ranking the BEV higher as compared to the basic car information case (Scenario 1). This finding also applies to PHEV as indicated by the positive coefficient sign. Furthermore, the marginal effect of providing 5-year fuel cost information on a respondent's choice probability is bigger for BEV than for PHEV, as indicated by the difference in the magnitude of coefficient value (i.e., 0.743 > 0.441).

Second, the marginal effect of providing both 5-year fuel cost and 5-year TCO information (Scenario 3) on a respondent's choice probability is much bigger for BEV than for PHEV, as indicated by model estimation results (i.e., 0.805 > 0.296).

Third, providing both 5-year fuel cost and 5-year TCO information (Scenario 3) does increase the probability of a respondent's ranking BEV higher as compared with providing 5-year fuel cost information case (Scenario 2). This is indicated by the difference in coefficient value between Scenario 3 BEV and Scenario 2 BEV dummies (i.e., 0.805 > 0.743).

Fourth, providing both 5-year fuel cost and 5-year TCO information (Scenario 3) is meaningful and could increase the willingness to choose PHEV, as compared to the basic car information case. Yet the marginal effect of providing both 5-year fuel cost and 5-year TCO information on PHEV choice probability is smaller than that of providing 5-year fuel cost information case, which is reflected by the estimated values of the Scenario 2 and Scenario 3 coefficients (0.296 < 0.441). This is presumably because, in our SP experiment settings, actual price, 5-year fuel cost, and 5-year TCO ($17,040) of BEV are all smallest among the three car options, and the insignificant TCO advantage of PHEV over CV ($18,548 vs. $20,810) may also interfere with a respondents' stated preference for PHEV.

Interestingly, the significant effect of providing 5-year fuel cost information on stated preference for EVs found by this study is consistent with a European study by Nixon and Saphores (2011). However, a U.S. study shows that the effect of providing 5-year fuel cost savings information is insignificant (Dumortier et al., 2015). This is probably because China and Europe are similar in their relatively high fuel price. In China, the gasoline price is nearly 1.5 times the U.S. average price. In Europe, the gasoline price is roughly double the U.S. average price. It is possible that car buyers in China and Europe are much more sensitive to fuel cost

Table 3
Estimation results of the rank-ordered logit model.

Variable	BEV		PHEV	
	Coefficient	z-value	Coefficient	z-value
Life cycle cost information				
Scenario 2	**0.743**	3.317	**0.441**	1.931
Scenario 3	**0.805**	3.585	0.296	1.309
Individual-level attributes				
Gender	**0.990**	5.130	**0.884**	4.596
Education	**0.294**	1.862	−0.143	−0.972
Numbercar	**−0.392**	−2.533	**−0.761**	−4.791
Distance	−0.111	−1.549	**0.164**	2.170
Desired price	−0.214	−1.565	**0.324**	2.366
Intercept	**−1.564**	−2.084	0.017	0.024
McFadden R^2: 0.29292				
Log likelihood: −741.89 −741.89				
Chi-Square: 614.67 (p = < 2.22e-16)				

savings information.

Last, in terms of individual-level attributes such as socioeconomic characteristics, our model shows that gender, education level, family car ownership, commuting distance, and desired price for a new car to buy, may have impacts on the ranking of the three car options. Specifically, (a) female respondents are more likely to rank BEV and PHEV higher; (b) respondents with higher education level are more likely to rank BEV higher; (c) respondents with more vehicles in their family may rank BEV and PHEV lower; (d) respondents with a longer commute distance are more likely to rank PHEV higher; (e) respondents who state they will buy a more expensive new car are more likely to rank PHEV higher.

In conclusion, this empirical study evidences the positive effect of providing 5-year fuel cost and 5-year TCO information on the stated preference for BEV and PHEV. Socioeconomic attributes such as gender, education level and family car ownership are found to have significant influence on Chinese consumers' EV purchasing intent. The study results have policy implications for EV promotion in China.

5. Conclusion and policy implications

Very few studies so far have explored the effect of providing total cost of ownership information on the electric vehicle purchasing intent of the 'below 40 or 45 young consumer' sub-population who account for the majority of the electric vehicle buyers. This study made the first attempt in exploring the effect of providing life cycle cost information on consumers' stated preference for battery electric vehicle and plug-in hybrid electric vehicle in the context of China. Using data collected from the stated preference experiment, the rank-ordered logit was developed to model consumers' stated choice among conventional gasoline vehicle, battery electric vehicle, and plug-in hybrid electric vehicle.

The positive impact of providing 5-year fuel cost and total cost of ownership information on the stated preference for battery electric vehicle and plug-in hybrid electric vehicle found by this study has policy implications. The study results suggest that it is worthwhile to initiate appropriate programs at various government levels to increase the awareness of the financial advantage of the electric vehicle fuel-economy technologies. Such programs may include various forms of awareness campaigns, governmental requirements to incorporate financial fuel-economy information of electric vehicles into a dealer's car information label.

This study shows that respondents with a high desired price are more likely to be willing to buy an electric vehicle. Respondents with low desired price are more likely to be those with low incomes, so if the price of electric vehicle can be lowered, then they may increase their willingness to buy electric vehicles. Price is an important factor of concern for car buyers, who prefer to buy a less expensive conventional gasoline vehicle than a more expensive electric vehicle (Shalender and Sharma, 2020). Automobile manufacturers should actively develop technologies to reduce the manufacturing cost of electric vehicles, thereby reducing the cost of selling electric vehicles and improving their competitiveness. In the experimental settings of this study, the actual price of plug-in hybrid electric vehicle and battery electric vehicle is almost the same with or lower than that of a conventional gasoline vehicle (i.e., about 26 thousand dollars for a conventional gasoline vehicle and a plug-in hybrid electric vehicle, and 24 thousand dollars for a battery electric vehicle) mainly due to the current subsidy from both state and local governments. An empirical study from Austria proves that government subsidies have indeed contributed to the expansion of the electric vehicle market (Priessner et al., 2018). However, the amount of subsidy for electric vehicles buyers at both state and local levels has decreased constantly in recent years. The decrease or even termination of subsidy for electric vehicles buyers may make electric vehicles be disadvantageous in terms of purchase price and thus increase the probability of ranking electric vehicles lower by a consumer. In this context, providing the fuel cost and total cost of ownership information is expected to play a more important and obvious role in increasing the probability of ranking electric vehicles higher by a consumer and in helping him/her make more informed electric vehicle purchasing decisions.

This study also shows that respondents with longer commuting distances are more likely to buy a plug-in hybrid than a battery electric vehicle, possibly due to mileage anxiety. Therefore, the government should accelerate the construction of charging piles and other infrastructure, provide certain financial support to relevant operators, improve the product certification and access management system for charging equipment, and pay attention to the safety management of charging infrastructure. At the same time, it should increase support for individuals to build charging piles and accelerate the construction of home charging piles. These measures have the potential to ease consumers' mileage anxiety and thus increase their willingness to purchase electric vehicles.

The significant impact of individual-level attributes such as gender and education level on electric vehicle purchasing intent might also be insightful in government policy and marketing strategy design and deployment for electric vehicle promotion. For example, when formulating consumer promotion measures, the government and enterprises should pay attention to grasp the differences in age, income and education level, etc., and develop differentiated and diversified electric vehicle promotion strategies for potential consumers at different levels.

The sample is somewhat inadequate because of time and funding constraints. In future research, a larger sample will be considered to enhance the rigidness of study results and hopefully reach more behavioral findings. A cross-city study using a larger sample of different cities will also be considered. With the varying government policies (e.g., monetary and non-monetary incentives) in China, further research on assessing the effects of providing life cycle cost information in various policy situations is warranted. In addition, more relevant variables (e.g., charging infrastructure and attitudes) will be included in future studies, and their possible interaction with providing life cycle cost information will be further explored. This will hopefully enhance the explanatory ability of the developed behavioral model and thus help to give a clearer and profounder picture of consumers' complex electric vehicle purchasing behavior.

The so far very small number of studies investigating the effect of providing life cycle cost information on electric vehicle purchasing intent in the literature suggests more studies are needed in this infant-stage research direction to advance the knowledge of consumers' complex electric vehicle purchasing decisions and to obtain more insights and implications for policy making and marketing. Cross-culture studies are welcome.

CRediT authorship contribution statement

Dandan Ji: Conceptualization, Methodology, Software, Visualization, Investigation, Writing – original draft. **Hongcheng Gan:** Data curation, Writing – review & editing, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A

Conventional Vehicle (Option A)

Engine capacity: 1.5T | Subsidy: none
Range: >= 450km | Sales tax: 7.5%
Maximum speed: 205km/h | Fuel consumption: 6.1L/100km

Actual purchase price: $25,978

Plug-in Hybrid Electric Vehicle (Option B)

Engine capacity: 1.5T | Subsidy: $5,076
Range: >= 450km | Sales tax: none
Maximum speed: 185km/h | Fuel consumption: 1.6L/100km
(Pure electric model: 13.5kW•h/km; Pure fuel model: 6.1L/100km)

Actual purchase price: $26,277

Battery Electric Vehicle (Option C)

Range: >= 300km | Subsidy: $11,048
Maximum speed: 185km/h | Sales tax: none
Power consumption: 13.5kW•h/km

Actual purchase price: $24,037

(a)

Conventional Vehicle (Option A)

Engine capacity: 1.5T | Subsidy: none
Range: >= 450km | Sales tax: 7.5%
Maximum speed: 205km/h | Fuel consumption: 6.1L/100km

Actual purchase price: $25,978 | ***Fuel cost: $3,434 (5years)***

Plug-in Hybrid Electric Vehicle (Option B)

Engine capacity: 1.5T | Subsidy: $5,076
Range: >= 450km | Sales tax: none
Maximum speed: 185km/h | Fuel consumption: 1.6L/100km
(Pure electric model: 13.5kW•h/km; Pure fuel model: 6.1L/100km)

Actual purchase price: $26,277 | ***Fuel cost: $896(5years)***

Battery Electric Vehicle (Option C)

Range: >= 300km | Subsidy: $11,048
Maximum speed: 185km/h | Sales tax: none
Power consumption: 13.5kW•h/km

Actual purchase price: $24,037 | ***Fuel cost: $836 (5years)***

(b)

Conventional Vehicle (Option A)

Engine capacity: 1.5T | Subsidy: none
Range: >= 450km | Sales tax: 7.5%
Maximum speed: 205km/h | Fuel consumption: 6.1L/100km

Actual purchase price: $25,978 | ***Fuel cost: $3,434 (5years)***
Total cost of owner: $20,810 (5years)

Plug-in Hybrid Electric Vehicle (Option B)

Engine capacity: 1.5T | Subsidy: $5,076
Range: >= 450km | Sales tax: none
Maximum speed: 185km/h | Fuel consumption: 1.6L/100km
(Pure electric model: 13.5kW •h/km; Pure fuel model: 6.1L/100km)

Actual purchase price: $26,277 | ***Fuel cost: $896(5years)***
Total cost of owner: $18,548 (5years)

Battery Electric Vehicle (Option C)

Range: >= 300km | Subsidy: $11,048
Maximum speed: 185km/h | Sales tax: none
Power consumption: 13.5kW•h/km

Actual purchase price: $24,037 | ***Fuel cost: $836 (5years)***
Total cost of owner: $17,040 (5years)

(c)

Fig. A.1. Car information labels in SP experiment: (a) Scenario 1, (b) Scenario 2, (c) Scenario 3.

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