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Agent-based modelling for market acceptance of electric vehicles: Evidence from China

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ABSTRACT

Inadequate consumer adoption has become a major obstacle to the diffusion of electric vehicles. Understanding and interfering with decision-making of these consumers may be the key to the acceptance of electric vehicles. In this study, an improved agent-based modelling is proposed to simulate the market acceptance of electric vehicles under multi-policy scenarios. The logic of consumer decision-making is portrayed by integrating consumer preferences, charging facilities, and the impact of government subsidies. The results show that the current consumers prefer plug-in hybrid electric vehicles and their attitude towards electric vehicles is more negative. A hybrid policy consisting of government subsidies and charging facility construction is the most effective strategy, where subsidies help stabilize consumption and charging facility construction facilitates the rapid electrification of vehicles in the current market. Moreover, increasing demand for sustainable consumption requires continuous upgrading of EV production technology. Based on these results, policy implications and suggestions for future electric vehicle industry are discussed.

1. Introduction

The electric vehicle (EV) industry has become the largest social sustainability movement and the most promising industry to reduce carbon dioxide emissions and dependence on oil (Wang et al., 2018b; Zhou et al., 2019). However, a major challenge to the development of a cleaner and sustainable society is the lack of consumer acceptance of EVs (Ullah et al., 2018; Li et al., 2020a). The early development of the EV industry is mainly based on the promotion of the public domain, such as public travel, urban sanitation and government vehicles. As the main battleground for the popularity of EVs, their penetration in the private passenger car market is still low, and the Chinese government wants EVs to succeed in this area (Wang et al., 2018a; Li et al., 2020a).

To encourage the adoption of EVs in the private passenger vehicle sector, China has enacted two important policies since 2012 – "*Energy-saving and new energy vehicle industry development plan (2012–2020)*" and "*New Energy Vehicle Industry Development Plan (2021–2035)*". These policies macro-planned future EV industry related guidelines, such as EV technology trajectory, business models, demand-led policies, and charging facility service levels. However, despite significant growth in EV ownership, its market share remains low and EVs are proliferating at a much slower rate than the government expects (Wang et al., 2018b; Li et al., 2020a). For example, by the first half of 2019, China had 250 m cars, of which only 1.37% were EVs. Consumers are caught in a state of "high attitude and cold behavior", i.e. they have a positive attitude towards buying EVs, but the real purchase rate is low, which also puts the country in an awkward pattern of "hot policies and cold markets" (Wang et al., 2018b; Li et al., 2020a). In view of this, further understanding of the social dynamics of EV proliferation from demand side may be central to breaking this stalemate.

Existing research has also attempted to understand and intervene consumer adoption decisions. These studies fall into two main categories, one to understand consumer influences on EV adoption, such as Wang et al. (2018b); Wu et al. (2019) and Ning et al. (2020); and one to understand the logic of consumer decisions on EV adoption, such as Silvia and Krause (2016); Zhuge et al. (2020) and Li et al. (2020a). In general, two consensus were reached, firstly, the importance of charging facilities for mass EV acceptance is identified; secondly, consumer decisions are the result of a combination of factors, i.e., consumer preferences, policy

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Notations

Symbol	definition
CE	cost-effectiveness of BEV.
pre_{BEV}	the BEV price premium.
sav_{BEV}	the lifetime operating cost savings of BEV.
c_{BEV}	BEV sales price.
s_{BEV}	the government subsidy for BEVs.
c_{CV}	CV sales price.
p_{oil}	the price per litre of petrol.
mpg_{CV}	the mileage per litre of oil.
oc_{BEV}	the cost of fully charge a BEV.
yer_{BEV}	assigned life cycle of a BEV.
r_{BEV}	the mileage of the BEV.
rc_h/rc_p	the probability of charging at home and in public charging facilities respectively.
oc_h/oc_p	the cost of charging at home and in public charging facilities respectively.
α_k	the influence of the social network on consumers.
$C(Q)$	the unit vehicle production cost when the vehicle output reaches
C_0	the initial production cost per unit of vehicle
α	the rate of technological progress of automobile manufacturers.
amt_{CV}/amt_{BEV}	the annual mileage of CVs and BEVs respectively.
E	the evaluation matrix of the expert group on the m product attributes.
S_k	matrix of consumers' preference weights for each attribute of m products.
μ	the mark-up on the product.

interventions and social networks, and individual micro-decision making will definitely affect EV diffusion (Eppstein et al., 2011; Ning et al., 2020; Song et al., 2020). However, to the best of our knowledge, conventional wisdom does not fully capture the complex social dynamics of EV adoption, and in particular, the logical role of charging facilities in consumer decision making is still missing.

To this end, this study aims to find effective strategies for the uptake of EVs in the field of private passenger vehicles from the perspective of complex adaptive systems. Understanding the necessary needs of consumers and depicting their decision-making logic are the premise of formulating effective policy interventions. An agent-based modelling (ABM) is used to simulate the dynamics behind the market acceptance of EVs by considering the dynamic interactions between governments, automakers and consumers. This study is interested in the following questions. First, what is the consumers' perception and social atmosphere about EVs? Second, is the government subsidy still the most important aspect for the acceptance of EVs? Third, how much impact have public charging facilities on the EV market? Can it be an alternative to government subsidies?

2. Literature review

Lack of consumer adoption in the private passenger vehicle segment has become one of the major barriers to the proliferation of EVs. Many studies have examined the topic of consumer adoption decisions, and these studies can be divided into three categories: consumer preferences, policy interventions, and EV diffusion.

The first stream investigates consumer preferences. Many empirical studies have provided theoretical support for consumer preferences, i.e., Ning et al. (2020); Li et al. (2020b) and Khan et al. (2020), these studies have examined the vast majority of consumer preferences regarding product attributes and policy interventions, including purchase price, operation cost, driving range, charging time, vehicle security, and related policies, such as purchase subsidy, carbon trading scheme and tradable driving credits. One of the key findings is that public charging facilities are key to supporting the mass acceptance of EVs (Santos and Davies, 2020; Tan and Lin, 2020). However, limited by the research method, i.e., discrete choice model, structural equation model and theory of planned behavior, these studies can only identify consumer car purchase preferences in terms of statistical correlation, but fail to capture the complex dynamics behind consumer decisions. This study contributes to this flow-through design consumer decision by integrating vehicle attributes, policy preferences, and facility impacts into a dynamic decision logic. Based on this, the vehicle preference attributes are presented in Table 1.

The second stream examine policy interventions. Policy interventions are also seen as an effective strategic tool to promote the development of EVs, but there is a great deal of uncertainty about the potential impact of such tools (Silvia and Krause, 2016; Sheldon and Dua, 2020). Take government subsidies as an example, Noori and Tatari (2016) indicated that EVs will account for 30% of the U.S. auto market by 2030, with BEVs accounting for the largest share, because of government subsidies. Wang et al. (2019) found that the abolishment of subsidies will reduce China's EV market share by 42%. However, Wang et al. (2018b) and Santos and Davies (2020) found that the impact of government subsidies on consumers' willingness to adopt EVs is not significant and limited. This suggests that the potential effects of policy are uncertain and that the optimal policy mix strategy still lacks sufficient evidence to support it. In light of this, this study contributes to a combination of Pareto efficient strategies, especially in combination with charging facility strategies, while providing more theoretical support for the potential effects of policy interventions that would promote the development of EVs.

The third stream is EV diffusion. The EV diffusion is the result of multi-agent and multi-factor combination. Discrete choice model, evolutionary game model and ABM are often used in the study in EV proliferation. For the first model, consumers consider the adoption behavior of EVs as the selection of a group of associated characteristics or properties of EVs. They make purchase decisions by assigning weights to the properties of different vehicles. For example, Ning et al. (2020) examined consumer' choice behavior of EVs by incorporating individual preference and network influence. Kim et al. (2020) used a discrete choice model to examine the effect of consumers' asymmetric preferences on their adoption decision, which uses the consumer's existing product as a reference point. For the second model, the consumer strategy choice mechanism under multi-agent interaction is the focus of its attention. Hu et al. (2020b) investigated the dynamic impact of different policies on EV diffusion by designing a complex network evolutionary game model. Li et al. (2019) uses a complex network evolutionary game to study the dynamic effects of government policies on the diffusion of EVs in networks of different sizes. However, in the first two methods, the discrete choice model emphasizes the importance of statistical relationships, and it is difficult to consider the influence of complex networks, while the evolutionary game model focuses more on the choice of game strategies of homogeneous individuals, reducing the complexity of the model. However, consumer decisions require information, not direct learning strategies (Li et al., 2020a). The environmental interaction and heterogeneous individual intelligence decision rules at the core of ABM set it apart from other modeling approaches, which makes it the most promising method for building complex system (Silvia and Krause, 2016; Zhuge et al., 2019). For exam-

Table 1
Consumer vehicle choice preference attributes.

Attributes		Attribute definition	Literature review
C1	Purchase price	The cost of buying a car	Lin and Wu (2018)
C2	Maintenance cost	The maintenance cost of a car for 8000 kms	Noori and Tatari (2016)
C3	Security	Comprehensive evaluation of automobile drives safety	Wang et al. (2018b)
C4	Technology integration	Evaluation of integration with information and communication technology and intelligent network connection technology	Li et al. (2020b)
C5	High power	Comprehensive evaluation of acceleration time of automobile at 100 km/h and matximum speed	Higueras-Castillo et al. (2019)
C6	Low noise	Comprehensive evaluation of noise generated in the process of automobile use	Higueras-Castillo et al. (2019)
C7	Carbon dioxide emission	Cars production of carbon dioxide per kilometer	Lin and Wu (2018)

ple, Zhuge et al. (2020) designed an agent-based integrated micro-simulation to analyze the potential influence of cost-related factors on the adoption of EVs. Sun et al. (2019) simulated the dynamic interactions between consumers and manufacturers to examine the impact of public subsidies on EV diffusion. Silvia and Krause (2016) used the ABM model to assess the impact of policy interventions on the proliferation of PHEVs. However, to the best of our knowledge, existing studies do not adequately capture the complex social dynamics of EV proliferation from the demand side, and in particular lack the logical role of charging facilities in consumer decisions. This study contributes to this literature stream by constructing a dynamic interaction between government, manufacturers, and consumers that integrates the effects of public charging facilities, social networks, and consumer preferences. Considering that this study model is a typical complex system model, ABM is also suitable for this study.

3. Methods

3.1. Model description

The purpose of this study is how to promote the electrification of vehicles in the private passenger car segment and achieve the conversion of consumer purchases from conventional vehicles (CVs) to EVs through the "scenario-response" method. Fig. 1 introduces a multi-agent framework that works year by year in programming software such as ANYLOGIC. There are three types of agents in the vehicle purchase simulation decision chart. Consumers make purchasing decisions to maximize their utility based on a combination of factors, such as consumer preferences, public charging facilities, social network impacts and policy interventions. Watts and Strogatz (1998) indicated that real-world interpersonal networks are characterized by small-world networks; thus, small-world networks are considered to be the most influential and commonly used networks. This study also uses small-world networks as the basis for consumer interaction networks. Automakers are to adjust production costs and selling prices by using technological learning. Manufacturers' production costs and sales prices will change in response to market demand for EVs, and EVs with changed sales prices will further influence consumers' willingness to buy them. The government agent, acting as a market regulator, specifies the number of subsidies for market-oriented charging facilities, the intensity of subsidies for EVs and the external market environment factors. Noted that public chargers only serve consumers within their service capabilities, and consumers who exceed their charger capabilities will no longer have access to

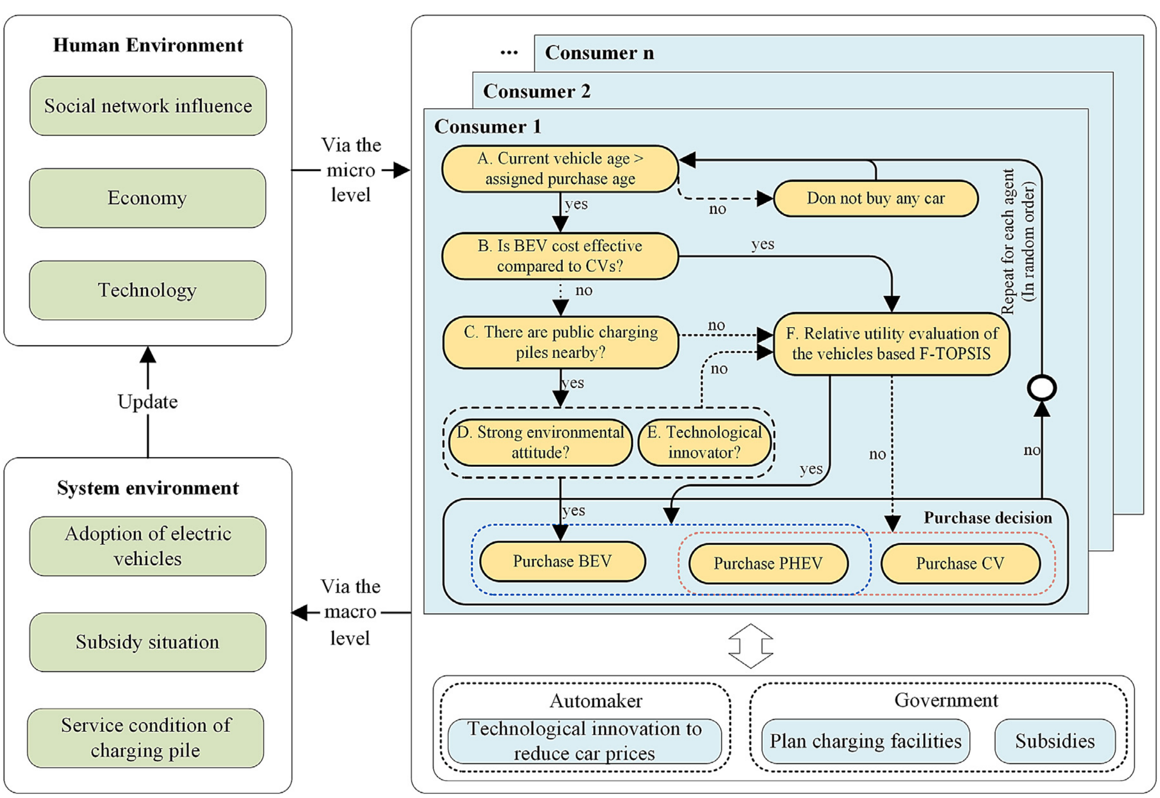

Fig. 1. The vehicle purchase simulation decision chart.

available public charging services, even if they may be close to the charger.

Assumptions of this model are as follows: (1) Information can be passed between individuals because there are social network connections and the social network structure remains constant throughout the diffusion process; (2) No major breakthroughs in EV technology and no major changes in consumer preferences will occur, so the study context remains unchanged throughout the experimental process; (3) The number of government subsidies for EVs is limited, and consumers will no longer be able to receive subsidies for purchasing EVs once the number of subsidies reaches the ceiling; (4) The external environment for vehicle purchases is stable and consumers will not delay purchasing a vehicle once they need to replace it with a new one.

3.2. Model

3.2.1. The purchase decisions of consumers

In this model, consumers have two important characteristics: heterogeneous preferences and bounded rationality. Because the purpose of this study is how to promote vehicle electrification in the private passenger vehicle segment and achieve the conversion of consumer purchases from CVs to EVs, this study assumes that consumers in the private passenger vehicle segment own at least one vehicle. Following the literatures, i.e., Eppstein et al. (2012), Silvia and Krause (2016) and Li et al. (2020a), this study designs a logical decision flow chart for consumers to describe the heterogeneous preferences of consumers. In addition, according to the fact that individual consumers make decisions by carefully considering all relevant aspects involved in the decision, but it does not matter which aspect is considered first, that is, there is no mandatory order. To this end, five key topics are designed to quantify consumer decisions. First, question A sets the premise of a potential consumer's decision to purchase a vehicle. Noted that a BEV may not be necessarily purchased when consumers need to buy a new car because their decisions depend on the answers to the remaining four questions in the decision logic.

Question B deals with the cost of EV adoption. If BEVs are cost effective relative to CVs, consumer agents will choose the ideal vehicle between BEVs and PHEVs based on the fuzzy TOPSIS method. Eq. (1) presents a cost-effective calculation method for each consumer, where the cost effectiveness of BEV CE is defined as the remainder of its price premium and lifetime operating cost savings, pre_{BEV} refers to the BEV price premium, sav_{BEV} is the lifetime operating cost savings of BEV, and yer_{BEV} is the assigned life cycle of a BEV. The price premium of BEV is shown in (2), where c_{BEV} is the sale price of BEV, s_{BEV} is the government subsidy for BEVs, and c_{CV} is the sale price of CVs. The lifetime operating cost savings is shown in (3), where p_{oil} is the price per litre of petrol, amt_{CV}/amt_{BEV} are the annual mileage of CVs and BEVs respectively, mpg_{CV} is the mileage per litre of oil, oc_{BEV} is the cost of fully charge a BEV, and r_{BEV} is the mileage of the BEV. Eq. (4) denotes the cost of a BEV to be fully charged once, rc_h/rc_p refer to the probability of charging at home and in public charging facilities respectively (*shown* in (5)), oc_h/oc_p refer to the cost of charging at home and in public charging facilities respectively.

$$CE = pre_{BEV} - sav_{BEV} \cdot yer_{BEV} \tag{1}$$

$$pre_{BEV} = c_{BEV} - s_{BEV} - c_{CV} \tag{2}$$

$$sav_{BEV} = p_{oil} \cdot \frac{amt_{CV}}{mpg_{CV}} - oc_{BEV} \cdot \frac{amt_{BEV}}{r_{BEV}} \tag{3}$$

$$oc_{BEV} = rc_h \cdot oc_h + rc_p \cdot oc_p \tag{4}$$

$$rc_h = \frac{oc_h}{oc_h + oc_p}, rc_p = 1 - rc_h \tag{5}$$

Noted that the model defaults to all consumers as "potential BEV adopters" who are classed as being able to take. Nonetheless, a "potential BEV adopter" does not necessarily imply that he/she will purchase or use a BEV. If individuals have enough motivations, they will make the decision to buy BEVs, otherwise they will choose other models. Questions C-E addresses these motivations. First, are there public chargers around consumer agents to meet their potential charging needs? In this study, the availability of public charging piles is regarded as a prerequisite for consumers' preference for EVs. If so, 2.5% of potential consumers are motivated by a personal desire to be at pioneers (or innovators) in technological advances and will buy BEVs (Rogers and Simon, 2003). Environmentalists and individuals who value the cutting edge of technology are often seen as niche groups willing to buy EVs, even if this is not "rational" from a purely cost perspective (Silvia and Krause, 2016). For simplicity, 16% of the consumers in the model are willing to buy BEVs, which is consistent with the value set by the Silvia and Krause (2016)'s study. However, if there is no charging facility around the individual or consumers' preferences are not met, they will choose between PHEVs and CVs based on the theory of maximum utility.

Question F defines the evaluation mechanism of consumer multi-vehicle choice based on the fuzzy TOPSIS method. Suppose the consumer has m choices of automobile products $P_1, P_2, \cdots, P_m$, and each product has n different attributes. The consumer weights each attribute based on the expert group's assessment of the vehicle. The consumer weight is S_k, expert group's evaluation is E and the influence of the social network on consumers is α_k. In this regard, the specific decision steps are as follows:

Step 1: Constructing multi-product attribute evaluation matrix E from expert group, and use e_{ij} to represent the j attribute value of the i product.

$$E = \begin{bmatrix} e_{11} & e_{12} & \cdots & e_{1n} \\ e_{21} & e_{22} & \cdots & e_{2n} \\ \vdots & \cdots & \vdots & \vdots \\ e_{m1} & e_{m2} & \cdots & e_{mn} \end{bmatrix} \tag{6}$$

Step 2: Constructing consumer matrix S_k based on the consumer product attribute matrix $w_k = (w_{1k}, w_{2k}, \cdots, w_{nk})^T$, where $S_k = E \cdot w_k$.

In reality, consumers often make purchase decisions based on their ambiguous perceptions. In this study, 7-point Likert scale is used to measure consumers' fuzzy perception and fuzzy TOPSIS method is introduced for decision analysis. Two types of language variable sets are used for evaluation: namely performance variable set and social network impact sensitivity variable set. Noted that these variable sets were also used in the perceptual evaluation of the expert group in step 1. Triangular fuzzy number is used to quantify consumer perception, as shown in Table 2.

Among them, the membership function $\mu_{\tilde{a}}(x): R \to [0, 1]$ of triangular fuzzy numbers is in (7):

$$\mu_{\tilde{a}}(x) = \begin{cases} \frac{x-a_1}{a_m-a_1}, & a_1 \le x \le a_m \\ \frac{x-a_n}{a_m-a_n}, & a_m \le x \le a_n \\ 0, & other \end{cases} \tag{7}$$

In the formula, the number of rows $\mu_{\tilde{a}}(x)$ indicates the degree to which element x belongs to fuzzy set $\tilde{a}$ and $a_1 \le a_m \le a_n$. The cascade average comprehensive representation is used to transform the fuzzy number into the exact value $P(\tilde{a})$, as shown in (8) and (9).

$$P(\tilde{a}) = (a_1 + 4a_m + a_n)/6 \tag{8}$$

$$P\left(\tilde{a} \otimes \tilde{b}\right) = [(a_1 + 4a_m + a_n)/6] \times [(b_1 + 4b_m + b_n)/6] \tag{9}$$

Table 2
linguistic variable set and triangular fuzzy number mapping.

Variable	Linguistic term						
Performance	Very Poor (VP)	Poor (P)	Mid-Poor (MP)	Fair (F)	Mid-Fair (MF)	Good (G)	Very Good (VG)
Sensitivity to social influence	Very Weak	Weak	Mid-Weak	Fair	Mid-High	High	Very High
Triangular fuzzy number	(0, 0,.1)	(0, 0.1, 0.3)	(0.1, 0.3, 0.5)	(0.3, 0.5, 0.7)	(0.5, 0.7, 0.9)	(0.7,.9,1)	(0.9, 1, 1)

In the formula, $\tilde{a} = (a_1, a_m, a_n), \tilde{b} = (b_1, b_m, b_n)$. Based on the above rules, the independent consumer k establishes a weight matrix $s^k = (x_{ij}^k)_{m\times n}$ for the weight $w_k = (w_{1k}, w_{2k}, \cdots, w_{nk})^T$ of n attributes $A_1, A_2, \cdots, A_n$ of the product automobile agent. Thus, the consumer weight is denoted in (10).

$$S_k = \begin{bmatrix} x_{11}^k & x_{12}^k & \cdots & x_{1n}^k \\ x_{21}^k & x_{22}^k & \cdots & x_{2n}^k \\ \vdots & \cdots & \vdots & \vdots \\ x_{m1}^k & x_{m2}^k & \cdots & x_{mn}^k \end{bmatrix} \tag{10}$$

In the formula, $x_{ij}^k = P(e_{ij} \otimes w_{jk}) = \frac{1}{6}(e_{ij}^1 + 4e_{ij}^2 + e_{ij}^3) \times \frac{1}{6}(w_{jk}^1 + 4w_{jk}^2 + w_{jk}^3)$,$e_{ij} = (e_{ij}^1, e_{ij}^2, e_{ij}^3)$ refers to the expert evaluation information for the j attribute of product i; $w_{jk} = (w_{jk}^1, w_{jk}^2, w_{jk}^3)$ refers to the preference of consumer k on product attribute j.

Step 3: Standardizing the consumer perception weight matrix, getting the normalization vector $\bar{x}_{ij}^k$, and the normalized matrix is calculated in (11), where $i = 1, 2, \cdots, m$ and $j = 1, 2, \cdots, n$.

$$\bar{x}_{ij}^k = \frac{x_{ij}^k}{\sqrt{\sum_{i=1}^m \left(x_{ij}^k\right)^2}} \tag{11}$$

Noted that the normalization matrix of the small-world network model was used to establish the influence of the social network on consumer adoption decisions:

$$\bar{x}_{ij}^k = (1 - \alpha_k)\bar{x}_{ij}^k + \alpha_k \sum_{l\in L_k} \frac{\bar{x}_{ij}^l}{|L_k|} \tag{12}$$

In the formula, α_k indicates the consumer's sensitivity to the social network influence; L_k indicates the number of directly connected neighbors of the consumer k; and $\bar{x}_{ij}^l$ is the normalized vector of the neighbor.

Step 4: Determining each consumer's ideal solution p^{k+} and anti-ideal solution p^{k-} according to the weight normalized value $\bar{x}_{ij}^k$:

$$p^{k+} = \left\{\bar{x}_1^{k+}, \bar{x}_2^{k+}, \cdots, \bar{x}_n^{k+}\right\} = \left\{\left(\max \bar{x}_{ij}^{k+} | j \in J_1\right), \left(\min \bar{x}_{ij}^{k+} | j \in J_2\right), |i = 1, 2, \cdots, m\right\} \tag{13}$$

$$p^{k-} = \left\{\bar{x}_1^{k-}, \bar{x}_2^{k-}, \cdots, \bar{x}_n^{k-}\right\} = \left\{\left(\max \bar{x}_{ij}^{k-} | j \in J_1\right), \left(\min \bar{x}_{ij}^{k-} | j \in J_2\right), |i = 1, 2, \cdots, m\right\} \tag{14}$$

In the formula, J_1 is the profitability index set, representing the optimal value on the i index; J_2 is the wastage index set, representing the worst value of the i index.

Step 5: Calculating the distance scale through the n dimensional Euclidean distance formula. The distance from the target to the ideal solution p^{k+} is d_i^{k+}, and the distance to the anti-ideal solution p^{k-} is d_i^{k-}, where $i = 1, 2, \cdots, m$:

$$d_i^{k+} = \sqrt{\sum_{j=1}^n \left(\bar{x}_{ij}^k - \bar{x}_j^{k+}\right)^2} \tag{15}$$

$$d_i^{k-} = \sqrt{\sum_{j=1}^n \left(\bar{x}_{ij}^k - \bar{x}_j^{k-}\right)^2} \tag{16}$$

Step 6: Calculating the closeness of the ideal solution:

$$C_i^k = \frac{d_i^{k-}}{d_i^{k+} + d_i^{k-}}, i = 1, 2, \cdots, m \tag{17}$$

In the formula, $0 \le C_i^k \le 1$. Noted that the goal is the worst if $C_i^k = 0$ and $p_i = p^{k-}$, and the goal is the best if $C_i^k = 1$ and $p_i = p^{k+}$.

Step 7: Sorting the closeness of the ideal solution C_i^k. The larger the value of closeness C^* is, the better the goal is. And the one with the largest value of C_i^k is the optimal decision-making goal.

3.2.2. The decisions of automakers

It is assumed that the EV automakers' technology matures over time and the cost of producing the car will decrease. Automakers make decisions about the price of vehicles based on current market demand and technical maturity. To this end, this study introduces a technical learning curve to depict the above process, which is denoted in (18).

$$C(Q) = C_0 Q^{-\alpha} \tag{18}$$

where $C(Q)$ is the unit vehicle production cost when the vehicle output reaches Q,C_0 is the initial production cost per unit of vehicle, and α is the rate of technological progress of automobile manufacturers. Thus, the learning rate is $1 - 2^{-\alpha}$, which is the percentage by which production costs will decrease when production is doubled. As for product pricing, assume that automakers use cost-plus pricing method. The sale price of the product i is measured in (19), where $\mu_i \ge 0$ refers to the mark-up on the product.

$$p_i = (1 + \mu_i)C_i \tag{19}$$

3.3. Simulation environment

This study was carried out in a virtual metropolitan environment with a volume of 200,000 vehicles, which was built on the basis of the city of Chongqing, China. Chongqing is an important first-tier city and municipality in China in terms of economic status and industrial volume. Chongqing's economic pillar is the automotive industry, with Changan, Lifan, Ford and other 14 vehicle manufacturers, 8 major auto brands, 1000 auto parts and accessories manufacturers together to develop the "1 + 8 + 1000″ industrial pattern, becoming one of the largest automotive production bases in China. Besides, Chongqing is also one of the first pilot cities in China to promote electric vehicles (published in 2013). The general public in Chongqing has a relatively good knowledge of EVs compared with other cities in China, so the virtual city built on the basis of Chongqing is a good representative. Based on the 0.168 cars per capita in Chongqing, this simulation environment is equivalent to a virtual city with 1.2 million people (Chongqing Municipal Bureau of Statistics, 2019). The model is scaled at 1:100, so 2000 cars represent the full 200,000. The study simulated a 360-square-kilometer space area, randomly generating consumer and public charging facilities. Every consumer needs to choose a car from BEV, PHEV and CV to meet their travel needs. In Fig. 2, the blue dot represents the consumer using the CV, the yellow dot represents the consumer using the BEV or PHEV, and the red rectangle is the public charging facility.

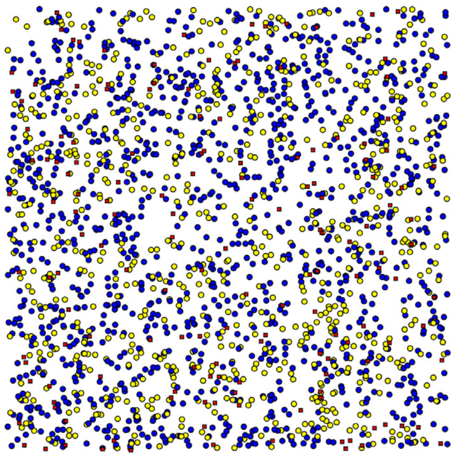

Fig. 2. Example simulation environment.

3.4. Scenario description

This study utilizes several policy intervention scenarios to analyze the potential effect that adjusting vehicle purchase price via government subsidies and expanding the public charging network will throw on the market acceptance of EVs. The baseline scenario means no policy intervention. Under the same amount of funding, the following four policy scenarios are contrived and their impact on the marketplace acceptance of EVs is examined. For simplicity, see Appendix A for scenario design rules.

1. Baseline scenario: No policy intervention;
2. Government subsidy scenario: Provide 330 subsidies worth RMB 18,000 (USD 2781) each, thereby reducing the purchase price of this number of BEVs;
3. Public charger scenario: Install 151 DC charging facilities and 227AC charging facilities at various locations in the city;
4. Hybrid policy: Use funds by providing 165 subsidies worth RMB 18,000 (USD 2781) and installing 75 DC charging facilities and 113 AC charging facilities in the city.

To evaluate their potential impacts, each scenario is simulated 30 times and their events (i.e. the number of EVs adopted, including BEVs and PHEVs) are averaged across all runs.

4. Results

4.1. Parameter initialization settings

The simulation parameters are taken from China's auto market for 2019 and 2020, including data released by government departments, survey results from existing literature, questionnaires, and realistic assumptions. This study selected the BYD Qin EV[1] as a representative model of the Chinese EV market. BYD Qin has three models: CV version, PHEV version and BEV version, the relevant parameters are shown in Table 3. Prior to the empirical research, potential EV consumer groups were identified, i.e. those with experience in using vehicles, already possessed a driving license, know about EVs or have plans to buy or use an EV in the next 3 years. The sample data was collected online in a snowball format, and we distributed the questionnaires to our colleagues and friends who were asked to distribute the questionnaires to their colleagues or friends (*see* Table 4, 5 and 6). In addition to the target group identification, two additional questions were set to remove unqualified respondents, 1) Is it possible for electric vehicles to be banned from travel by traffic control? 2) Do you live in the city of Chongqing? Those who answered yes to the first question and no to the second question will be deemed ineligible. Finally, questionnaire was conducted in May 2020 and a total of 243 valid questionnaire data (320 total sample size) was obtained with an effective questionnaire rate of 75.9%. The questionnaire constructs and demographic characteristics are attached in Appendix B. As for Table 4, experts from Chongqing Automotive Synergy Center and Changan Automobile were visited to obtain expert group vehicle evaluation data. Through the fuzzy transformation of the data set, the expert group's product feature evaluation matrix (*see* Table 4), consumer product preference attribute perception matrix (*see* Table 5) and consumer social network sensitivity (*see* Table 6) are obtained.

[1] BYD Qin is a best-selling electric vehicle released by BYD, and it is the highest rated vehicle in the top 10 of China's electric vehicle market sales in 2020

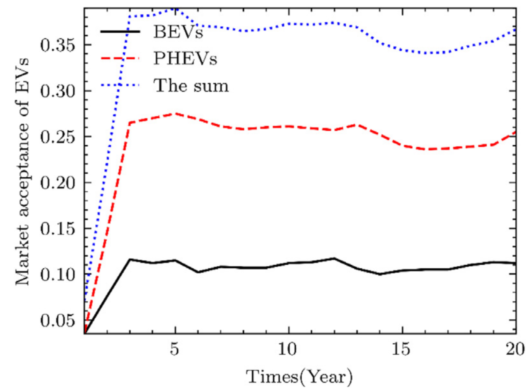

Fig. 3. Market acceptance of electric vehicles under the baseline scenario.

4.2. Results of the electric vehicle choice behavior diffusion

After obtaining the model data parameters, all simulation experiments are conducted in ANYLOGIC 8.7.2, including multi-policy scenario simulation experiments and sensitivity analysis experiments. The baseline scenario is used to show the situation of consumer EV choice behavior. In Fig. 3, the average market acceptance of BEVs and PHEVs was run thirty times to obtain. Judging from the overall evolutionary trend of the baseline scenario, the growth trend of PHEVs is much higher than that of BEVs. The whole evolution process is an S-shaped growth curve, which is consistent with the diffusion curve of new product innovation proposed by Rogers et al. (2003). Although the initial proportion of BEVs is four times that of PHEVs, the growth speed of PHEV market acceptance is much higher than that of BEVs. When reaching equilibrium, the market share of EVs is 36.7%, including PHEVs for 25.5% and BEVs for 11.2%. These results indicate that, for the vast majority of consumers in the field of private passenger cars, they prefer to adopt PHEVs rather than BEVs.

Fig. 4 shows the evolution of EVs under different policy interventions. Governments can adopt different strategies to guide the acceptance of EVs. Specifically, the policy hybrid scenario has the greatest acceptance of EVs on the market, second only to subsidy scenario and public charger scenario, and finally to the baseline scenario. The impact of public charging facilities and subsidies reported in Fig. 4 appears to be different, with charging facilities having significantly greater incentives in the early stages than subsidies, but the final evolution of the two appears to be similar. The subsidy policy for charging facilities may be an effective substitute for the subsidy policy for EVs. In addition, compared with the simple EV subsidy or a charging facility subsidy scenario, the combination of the two policies is the most effective scenario to promote the development of EVs.

Table 3
The initial value setting of the model. (Refer to (China statistics press, 2019), China Electric Vehicle Charging Infrastructure Promotion Alliance (EVCIPA), 2020, questionnaire, Silvia and Krause (2016), (Rogers and Simon, 2003)).

Attribute	Explanation	Values
Initial rate of EVs	According to the ratio of PHEVs to BEVs in China's EV industry is about 4:1, the initial ratio of EVs is assumed to be 2%, including 1.6% for BEVs and 0.4% for PHEVs.	2%
Daily travel distance	Consumer day travel distance is subject to a triangular distribution.	T (20, 80, 32) km
Vehicle age	The age of each consumer agent is determined by randomly assigning values that follow a triangular distribution.	T (24, 60, 36) months
Assigned vehicle age	The preset maximum service time of a vehicle.	60 months
Sale price of BEV	Pre-subsidy automaker's suggested retail price for BEVs, referenced from BYD Qin EV.	RMB 167,900 (USD 25,991)
Battery capacity	Maximum number of energy that can be accommodated by a BEV.	42 kWh
Mileages per unit of energy	Calculated by the vehicle's energy consumption of 100 km, of which the BEV is 7.55 miles and the CV is 16.13 miles	7.55/16.13 miles
Subsidy for BEVs	Government subsidizes RMB 18,000 per BEV.	RMB 18,000 (USD 2781)
Subsidy for AC/DC	Subsidies of RMB 36,000 per DC and RMB 2100 per AC.	RMB 36,000/2100 (USD 5573/325)
Charging facility service capabilities	The average daily service number of fast charging pile DC is 6, and the average daily service number of slow charging pile AC is 2.	6/2
Oil price	The price per litre of petrol.	RMB 6.5 (USD 1)
Sale price of CVs	The selling price of fuel vehicle, reference from BYD Qin fuel vehicle.	RMB 79,800 (USD 12,353)
Rate of technological innovation	The rate of technological progress of automakers	0.08
Rate of mark-up	The mark-up on the product.	10%
Electricity price	At home 0.65 RMB/kWh, public facilities 1.5 RMB/kWh.	RMB 0.65/1.5 (USD 0.1/0.23)
Number of charging facilities	Based on the matching ratio of 3.5:1 for EVs to charging posts, the 2000 agents should have 158 charging facilities, and according to AC and DC 3:2, there are 95 AC and 63DC.	158
Innovativeness	2.5% of the population have a preference for technological innovation and are willing to adopt new technologies.	2.5%
Environmental attitude	The 16% of consumer agents with the highest environmental score are considered as environmentalists.	16%

Table 4
Product information created by an expert group.

Model	Attributes						
	Purchase price	Maintenance cost	Security	Technology integration	High power	Low noise	Carbon dioxide emission
BEV	F	F	F	G	MF	G	G
PHEV	F	MF	MF	MP	G	MF	F
CV	G	MF	MF	MP	F	F	MP

Notes: P, Poor; MP, Mid-Poor; F, Fair; MF, Mid-Fair; G, Good.

Table 5
Consumers' weights on seven attributes.

Weight	Attributes						
	Purchase price	Maintenance cost	Security	Technology integration	High power	Low noise	Carbon dioxide emission
Very Poor	.0092	.0046	0	.0367	.0092	.0046	.0505
Poor	.0046	0	0	.0642	.0275	.0183	.0550
Mid-Poor	.0229	.0550	.0046	.1376	.0826	.0413	.1284
Fair	.1055	.1468	.0275	.1881	.2615	.1468	.1881
Mid-Fair	.2798	.3440	.1376	.2752	.3349	.3119	.2523
Good	.2661	.2890	.2064	.2202	.2202	.3486	.2294
Very Good	.3119	.1606	.6239	.0780	.0642	.1284	.0963

Table 6
Consumer's sensitivity levels of social influence.

Sensitivity level	Very High	High	Mid-High	Fair	Mid-Weak	Weak	Very Weak
Relative frequency	.0872	.2064	.3899	.1835	.0917	0	.0413

4.3. Sensitivity analysis

4.3.1. Impact of social networks

Consumers do not exist in isolation, and they are often influenced by social networks when making purchase decisions. In reality, consumers are more willing to refer to "word-of-mouth" of products, friend recommendations, and have a certain mentality of conformity (Kim et al., 2011; Ning et al., 2020). In this experiment, the policy hybrid scenario was used to analyze the impact of social networks on the EV diffusion. Fig. 5 shows that as the influence of social networks increases, the rate of EV diffusion (including BEVs and PHEVs) decreases significantly. In words, the market acceptance of EVs is negatively related to the impact of social networks, which are not conductive to the diffusion of EVs.

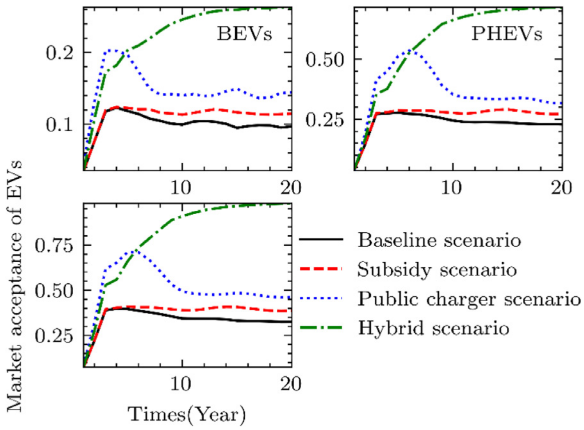

Fig. 4. Market acceptance of electric vehicles under four policy scenarios.

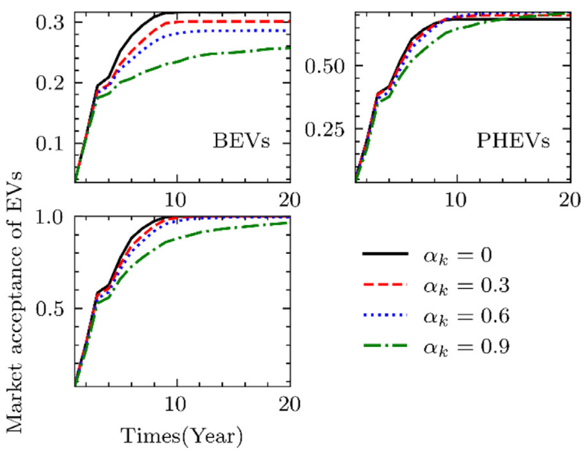

Fig. 5. The impact of social network on the market acceptance of electric vehicles.

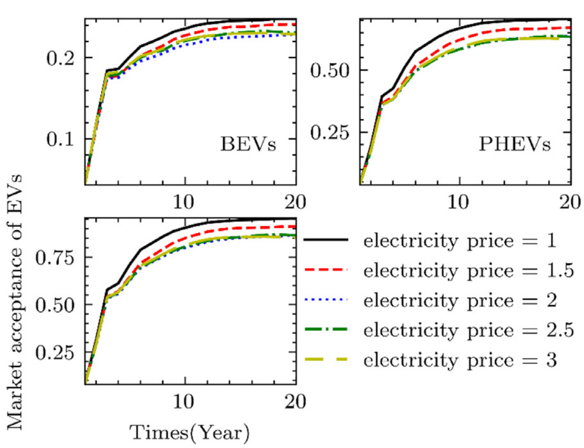

Fig. 6. The impact of electricity prices on the market acceptance of electric vehicles.

4.3.2. Impact of electricity and oil price

Fig. 6 and 7 represent the impact of electricity and oil prices on the proliferation of EVs, respectively. The results show that an increase in the price of electricity is inversely proportional to the proliferation of EVs, and an increase in the price of oil is positively proportional to the proliferation of EVs. Obviously, this conclusion is consistent with our intuition, but it is worth noting that two findings have important implications for social practice. First, the countervailing force of electricity and oil prices may be a balancing policy to drive the conversion of private passenger vehicles from

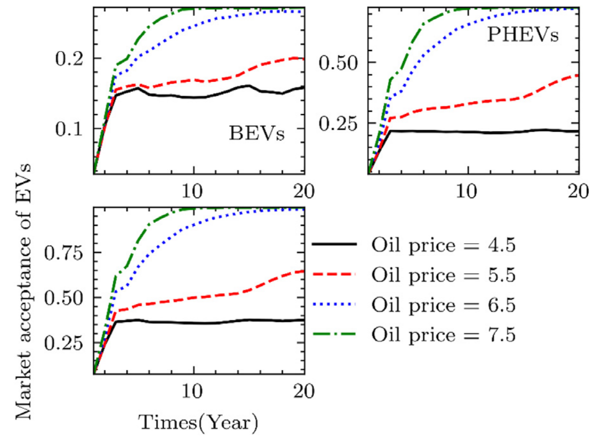

Fig. 7. The impact of oil prices on the market acceptance of electric vehicles.

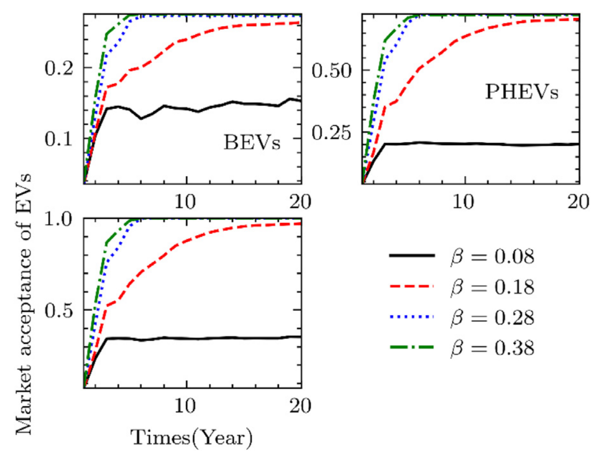

Fig. 8. The impact of technology learning rate on the market acceptance of electric vehicles.

CVs to EVs. Second, while this balancing act facilitates the electrification of vehicles, it does not facilitate the conversion of vehicles from PHEVs to BEVs.

4.3.3. Impact of technology learning rate of manufacturers

Fig. 8 shows that the impact of technology learning rate on the EV diffusion. The technology learning rate of manufacturers is positively related to the promotion of EVs. Technology learning has reduced the cost of producing cars for EV manufacturers, prompting increased willingness to adopt EVs. It is worth noting that as the cost of producing EVs has decreased, sales of PHEVs have increased even more, despite the significant increase in BEV sales. This suggests that the cost reduction of EVs is not sufficient to drive the conversion of PHEVs to BEVs, but contributes to the reduction of CVs in the market. More non-financial incentives are needed in the process of achieving electrified road vehicles.

5. Discussion

Expanding the market share of EVs in the private passenger car segment has become one of the most important issues in society today. A deeper understanding of the decision-making logic of consumers in the private passenger vehicle sector is important for the development of EV proliferation intervention policies. To this end, the discussion is analyzed in two parts based on the simulation results, namely policies and consumer demand.

5.1. The analysis of policies

Clean energy and technology diffusion are generally policy-relevant, and this study yielded three policy-relevant findings. (1) The effect of vehicle purchase subsidy policy is relatively weak, and its effect is not as obvious as the effect of subsidizing charging facilities. (2) Mixed policy incentives are better than any single policy. (3) The inverse force of electricity and oil prices is a good balancing policy.

In terms of policy uncertainty, the findings of this paper further support the argument from (Wang et al., 2017, 2018b) and agree that the effect of subsidy policies is diminishing. A possible explanation for this might be that the mass still regards the EV as a tool to meet their travel needs, in which meeting charging needs is a basic or must-be attribute and the government subsidy is attractive attribute (Yang et al., 2015). Government subsidy is their attractive attribute, and its impact on consumers is not as great as expected. And about 25% of the Chinese masses cite subsidies as the main factor influencing their purchase of an EV, and while significant, the convenience factor is more important to consumers (Wang et al., 2017). Thus, the existence of government subsidies will improve consumer satisfaction, but if it is not provided, it will not cause consumer dissatisfaction (Yang et al., 2015; Li et al., 2018). On the contrary, meeting the charging demand is the basic condition for private passenger car consumers to adopt EVs and they are also more willing to pay more for the use of charging services or charging facilities (Tan and Lin, 2020). If this demand is not met, they will be very dissatisfied and unwilling to use EVs. This also reveals why supporting public charging infrastructure is the key to the mass acceptance of BEVs, while the effect of government subsidies is limited (Neaimeh et al., 2017; Santos and Davies, 2020). To sum up, the influence of high EV subsidies is limited and will not lead to the long-term success of the EV market (Harrison and Thiel, 2017; Song et al., 2020).

Of course, this does not mean that the government should abandon the subsidy policy and just subsidize charging facilities. This study shows that mixed policies perform better than single policies. According to Wang et al. (2019), China's phasing out of subsidies led to a 42% drop in EV market share. Such a drastic drop in demand for EVs is bound to be detrimental to the development of the charging facility industry as well, as the two are in a circular cause-and-effect relationship. Given this relationship, perhaps a buffer phase could be added to mitigate the dramatic impact of EV subsidies on the system as a whole, i.e., subsidizing both EVs and charging facilities. However, it seems that the Chinese government prefers to promote EVs before developing charging facilities, with the two being promoted independently and the mutual causal relationship between them being ignored. This is the reason why the reduction of EV subsidies has led to a sharp drop in market share in the short term, and more importantly this is also extremely detrimental to the promotion of the charging facility industry. To this end, a buffer phase may be an effective strategy and this study provides theoretical support for the scientific validity of this strategy.

Finally, the policy of balancing oil and electricity prices needs to be taken seriously. Although the role of electricity and fuel prices has been identified by many studies, and these two factors are indeed cost factors that influence consumers' vehicle choices, the rational use of these two influencing factors has not been considered in depth, and there is a lack of rational application of this power in real-life applications (Li et al., 2019; Hu et al., 2020a). In China, the service price of charging facilities is not regulated by the government, and fewer charging facilities enterprises have not yet formed a competitive pattern, and the local monopoly is not conducive to reasonable competition in tariff (Zhang et al., 2019; Zhao et al., 2020). Therefore, reasonable tariff setting is still a problem that has yet to be solved and directly affects the market acceptance of EVs. In this regard, the government and enterprises should pay attention to the rational setting of electricity prices while also adopting a balanced electricity-oil price policy strategy to provide an external environment for the implementation of a more attractive electricity price strategy.

5.2. The analysis of consumer demand

As a high-cost durable product, the purchase decision of EVs is inevitably influenced by consumer preferences and externalities such as product word-of-mouth and advice from friends. Three important findings are obtained. (1) Consumers prefer PHEVs to BEVs. (2) Current consumer attitudes about EVs in the private passenger car segment are negative, creating a negative social network atmosphere that is not conducive to the proliferation of EVs. (3) Increasing demand for sustainable consumption requires continuous upgrading of EV production technology.

In terms of the first point, there may be two reasons for this phenomenon: first, it may be related to barriers to the adoption of BEVs, such as a BEV range limitation that is not relevant for PHEVs (Silvia and Krause, 2016); second, it may be related to China's policy guidance. In China, PHEVs are also regarded as a type of EVs, belongs to clean vehicle (Zhou et al., 2019), and is an intermediate product to realize the transition from CVs to BEVs. This means that many supportive policies of BEVs also support PHEVs, such as exemption from road tolling or bus lane access, attracting more consumers to adopt PHEVs (Wang et al., 2019). Thus, from the perspective of consumer utility theory, PHEVs have more advantages in comprehensive use and policy benefits than BEVs. However, considering that the PHEV is a transitional product in China, its policy support should be weakened or removed at a later stage. Before a major breakthrough in BEV battery technology, the government should adhere to the strategy of PHEVs as a transitional product, which does not conflict with the travel needs of consumers in the field of private passenger cars and has the opportunity to achieve a lot of potential PHEV purchasing demands. EV enterprises can also take the PHEV market as the service object to obtain more financial support for the breakthrough of BEV technology while developing battery technology.

The second finding is unexpected and a possible explanation for this might be that consumers still have a relatively negative understanding of EVs, perceive more risks, such as slow charging and inconvenient charging, and do not advise people around them to use EVs (Wang et al., 2018b). In China, consumers' knowledge about EVs is stereotyped and fixed, and till stays in the stereotype of EVs (vehicles + batteries + government policies). Lacking of knowledge about EVs and perceiving high risk of EVs have become a significant psychological obstacle hindering consumers' acceptance of EVs, especially in the current situation of phasing out subsidies (Wang et al., 2018b). Consumers are caught in a state of "high attitude and cold behavior", i.e. they have a positive attitude towards buying electric vehicles, but the real purchase rate is low, which also puts the country in an awkward pattern of "hot policies and cold markets" (Wang et al., 2018b; Li et al., 2020a). This negative effect can be reflected in the market acceptance of both BEVs and PHEVs (*see* Fig. 5). Therefore, public cognitive bias about EVs still exists (Lin and Wu, 2018). It is necessary for governments to design more activities and more reasonable policies to guide consumers' awareness of EVs and improve the physical use environment of EVs, such as the layout and operation of charging piles.

Finally, the third finding is also easy to understand. Many studies have shown that high costs are one of the major factors hindering the proliferation of EVs (Junquera et al., 2016;

Wang et al., 2018b). However, the cost of EVs is not only related to their R&D investment cost, but also to their production cost. The current EV market in China is only 1.37% of the total market, and most automakers are very focused on investing in R&D for EVs, while neglecting the technological upgrading of the production line itself. The low production demand makes the production cost of EVs more expensive compared to CVs, and the mixed production of CVs and EVs also makes the production technology more complex. Therefore, the improvement of production line technology for EVs is an important practical issue, and the findings of this study suggest that the improvement of production line technology for EVs can help the proliferation of EVs. To this end, the government and manufacturers should pay attention to the improvement of production line technology while actively guiding the generation of consumer demand, such as formulating relevant policies to support, or benchmarking relevant technology companies to promote advanced production technology.

6. Conclusions

Promoting consumer adoption of EVs is critical to building a clean and sustainable society. This study proposed an agent-based simulation model considering the effects of public charging facilities, consumer preferences and social networks. The proposed model aims to examine the comparative impact of different policy interventions on the market acceptance of EVs to promote the popularity of EVs.

This study is novel in the following regards. First, a novel consumer decision logic is portrayed by integrating the impact of public charging facilities, consumer preferences and social networks. Existing studies only show that public charging facilities are statistically positively related to consumers' willingness/attitude to adopt EVs, but the role of public charging facilities in consumer decision-making remains unclear. Second, a new EV diffusion dynamics is proposed by integrating the effects of public charging facilities, manufacturer technological innovation, and government policy intervention on consumer adoption decisions. This study is particularly innovative in integrating the effects of charging facilities in the dynamics of EV diffusion. Third, new policy intervention portfolio strategies were designed and evaluated based on an improved EV dynamics model. This provides more theoretical supports for the assessment of the uncertainty of the current policy effect.

The main findings and suggestions of the study are as follows. First, consumers are more inclined to PHEVs in the choice of EVs, so the governments should adhere to PHEVs as transitional products to realize the transformation of consumer demand from CVs to EVs. Second, the planning and deployment of the public charging facilities are conductive to the mass acceptance of EVs and subsidies for public charging facilities are an effective alternative to EV subsidies. Governments and enterprises should actively formulate policies to develop and operate public charging infrastructure. Third, compared with the simple EV subsidy or the charging facility subsidy scenario, the combination of the two policies is the most effective scenario to promote the development of EVs. This means that the government can shift EV subsidies to a state where the two coexist, looking for the most effective Pareto policy mix strategy. Fourth, the social network atmosphere of consumers about EVs is still relatively negative, and their perceived bias about EVs still exists. At present, it seems that this is a relatively serious problem. The government and enterprises should actively guide consumers' awareness of EVs and change their inherent prejudice against EVs, which may be the premise of large-scale adoption of EVs. Finally, EV manufacturers should try to improve their technology to gain more market share, and governments should not rely too heavily on regulatory strategies related to CV usage costs.

Some restrictions still exist due to the complexity of practical problems. First, this study mainly focuses on the market acceptance of EVs in the field of private passenger cars, without considering the public domain. In reality, the diffusion of EVs in the public domain played a vital role in the development of early EVs. Second, the knowledge of consumer evaluation involved in the study is a short-term knowledge that influences consumer vehicle decision-making and remains relatively constant throughout the cycle. Future research can analyze the evolution of consumer knowledge in different technical contexts to achieve the effectiveness of long-term decision-making.

Declaration of Competing Interest

None.

Acknowledgments

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Appendix A. Scenario design

Baseline scenario: Based on China's 3.5:1 match rate between EVs and charging facilities in 2019, the ratio of fast charging facilities to slow charging is 2:3, and the assumption of their service capability, the 2000 agents in the basic scenario should have 158 charging facilities.

Government subsidy scenario: According to BYD's official website, a BYD Qin EV can receive a subsidy of RMB 18,000 (USD 2781) in 2021.

Public charger scenario: In China, different local governments have different construction subsidies for charging pile construction, and the subsidy standard is based on a certain proportion of power (AC / DC) or total investment. Considering that the construction object of this paper is distributed DC charging pile (DC, 60kw) and AC charging pile (AC, 7kw), so the subsidy standard adopts the method of power distribution. In most provinces, dc charging piles are subsidized at 400–900 RMB/kW (61.2–139.3 USD/kW), and most are 600 RMB/kW (61.2 USD/kW), while AC charging piles are subsidized at half the amount of DC charging piles. Therefore, the subsidy amount for each DC charging pile is RMB 36,000 (USD 5573), and the AC charging pile is RMB 2100 (USD 325). According to China's Charging Infrastructure Development Report 2019–2020, the ratio of China's charging pile DC to AC is 2:3. Thus, scenario 3 assumes that the government will provide subsidies for 151 DC charging facilities, each worth RMB 36,000 (USD 5573), and 227 AC charging facilities, each worth RMB 2100 (USD 325).

Appendix B. Questionnaire constructs and demographic characteristics

Tables B1 and B2

Table B1
Questionnaire constructs.

Factors	Measurement items
Purchase price	I think the price of a vehicle is very important to the decision I make to purchase the vehicle.
Maintenance cost	I think the maintenance cost is very important to the decision I make to purchase the vehicle.
Security	I think technology security is very important to the decision I make to purchase the vehicle.
Technology integration	I think technology integration (i.e. imbedding more vehicle technologies) is very important to the decision I make to purchase the vehicle.
High power	I think high power is very important to the decision I make to purchase the vehicle.
Low noise	I think low noise is very important to the decision I make to purchase the vehicle.
Carbon dioxide emission	I think low carbon dioxide emission is very important to the decision I make to purchase the vehicle.
Social network influence	I think the influence of the circle of friends (e.g., a friend's recommendation or a friend's decision to buy a car) is important to my car purchase decision.

Table B2
Demographic characteristics.

Characteristics	Number	Ratio (%)	Characteristics	Number	Ratio (%)
Gender			5001–10,000	58	23.87
Male	126	51.85	10,001–15,000	31	12.76
Female	117	48.15	>15,000	22	9.05
Age (In years)			*Occupation*		
<18	3	1.23	Student	50	20.57
18–24	74	30.45	Business	49	20.16
25–34	112	46.09	Public servant	44	18.1
35–44	40	16.46	Manufacturing and Engineering	67	27.59
45–65	14	5.76	Other	33	13.58
Education Level			*Marriage*		
High school or below	8	3.29	Unmarried	83	34.15
Bachelor	126	51.85	Married	160	65.85
Master	74	30.45	*Family size*		
Ph.D.	35	14.4	1–2 members	31	12.76
Monthly Income (RMB)			3 members	78	32.1
<3000	96	39.51	4 members	81	33.33
3001–5000	36	14.81	5 members and more than	53	21.81

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