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An Agent-Based Modeling Approach for the Diffusion Analysis of Electric Vehicles With Two-Stage Purchase Choice Modeling

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Diffusion research of innovative technologies is crucial for new product positioning and strategic planning in product design. As a versatile system simulation method, agent-based modeling (ABM) has been used in many previous studies on the diffusion analysis of electric vehicles (EVs). In these simulations, modeling consumers' purchase decisions is a significant step. Previous studies often adopt simple rule-based decision criteria in this step, while an accurate purchase decision model can contribute to a more reasonable diffusion analysis of EVs. To fill this gap, this brief presents an agent-based modeling approach for the diffusion analysis of electric vehicles with two-stage choice modeling. The core idea is to separate consumers' decision-making process for purchasing cars into two stages. Consumers first form a small choice set from the whole auto market. Then, they make the final choice from the choice set built in the first stage. In addition, the word-of-mouth (WOM) effect and consumers' social networks are also considered in the ABM, which can further improve the accuracy of the diffusion analysis. A case study using data collected from Shanghai, China, is presented to demonstrate the proposed approach. Our approach outperforms other ablation models as well as traditional statistical models in the prediction accuracy of EV's market share. The influence of factors such as government policy and technological improvement on the diffusion of EVs is also discussed. These insights can assist automakers in improving their product design and enhancing their market competitiveness.
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Keywords: agent-based modeling, technology diffusion, consumer preference, two-stage choice modeling, consumer social network, data-driven engineering

1 Introduction

Diffusion studies of innovative technologies are essential for product positioning and strategic planning in new product design [1,2]. In the past decade, the diffusion analysis of electric vehicles (EVs) and plug-in electric vehicles (PHEVs) has attracted increasing attention from automakers and market regulators. Important factors influencing consumers' adoption rates and the diffusion of electric vehicles include vehicle range, charging time, and price [3,4]. For the stakeholders in the EV industry, knowing how these factors will impact consumers' purchase decisions can greatly support the development of next-generation EVs with higher competitiveness. Therefore, appropriate tools and models are needed to quantify the impact of these factors and predict their future influence.

As a versatile system simulation method, agent-based modeling (ABM) has been used in many previous studies as it enables convenient modeling and investigation of the interdependencies of stakeholders in the EV market (i.e., agents), including consumers, vehicle manufacturers, and government agencies [5,6]. In these simulations, modeling consumers' purchase decisions is a significant step, as its results can directly influence the accuracy of the diffusion analysis. Previous studies either use rule-based decision criteria or utility-based methods such as discrete choice analysis (DCA) in this step. These studies oversimplify the decision-making process of consumers, neglecting that consumers often make decisions in multiple stages, especially when they face a market with numerous products [7,8]. Thus, an improved purchase choice model can contribute to a more accurate diffusion analysis of EVs.

To fill this gap, we propose an agent-based modeling approach for the diffusion analysis of electric vehicles with two-stage choice modeling. The core idea is to separate consumers' decision-making process for purchasing a car into two stages [9]. Consumers form a small choice set from the whole auto market in the first stage. In the second stage, consumers make the final choice from the choice set built in the previous stage. In addition, the word-of-mouth (WOM) effect and consumers' social networks built based on their income and residential locations are also considered in the ABM, which can further improve the accuracy of our model.

A case study employing data collected from Shanghai, China, is presented to demonstrate the proposed approach. Compared with the two ablation models (one without a two-stage choice model, the other without consumers' social network) as well as the traditional linear regression model and time-series model, our proposed approach shows better accuracy in predicting EV's share in the market. We also investigate the impact of key market, consumer, and product factors on the diffusion of EVs with what-if scenario tests. Our work contributes to the development of a more accurate diffusion analysis model for EVs and a more comprehensive understanding of how market, consumer, and product factors influence the adoption of EVs. These insights can support automakers to further improve their product competitiveness.

The rest of this technical brief is organized as follows. Section 2 reviews previous work on agent-based modeling and its usage in EV diffusion analysis. Section 3 introduces the proposed methodology and explains the implementation details. Section 4 presents the case study using data collected from the Shanghai auto market.

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Section 5 provides the case study results, including the ABM simulations, benchmark analysis, and related what-if scenarios tests. Section 6 concludes the study and suggests possible future research directions.

2 Related Work

Technology diffusion is defined as the process in which a new technology spreads throughout a society or market [10]. The significance of technology diffusion research lies in its ability to provide insights into how new technologies are adopted and how they can be effectively marketed to accelerate their diffusion [11]. Among various modeling methods, ABM has been used in many previous studies to investigate technological diffusion [12,13] as it can model the interactions between individual agents and capture the emergent behaviors that result from these interactions.

For example, Klein et al. [14] proposed an ABM-based approach for analyzing the impact of charging infrastructure on the diffusion of EVs. Compared to conventional vehicles (CVs), the diffusion of EVs is influenced by certain unique factors, such as the availability and accessibility of charging stations, as well as the range of EVs. However, they neglected the impact of government policies and incentives on the diffusion process. Zhang et al. [5] proposed an ABM-based approach for analyzing the factors that influence consumers' adoption of EVs, such as consumer preferences, charging infrastructure, and government policies, but ignored the impact of automotive manufacturers' launching new vehicles and pricing strategies. Zadbood and Hoffenson [15] proposed an ABM-based approach for analyzing the impact of social influence on the diffusion of EVs. However, they lacked considering the impact of government policies and incentives on the diffusion process. Zhang et al. [16] proposed an ABM-based approach for analyzing the impact of ride-sharing services on the diffusion of EVs. They modeled factors such as the availability of ride-sharing services, the cost of using such services, and the range of EVs but failed to consider the influence of new vehicles entering the market.

In addition, previous studies often use rule-based decision criteria or utility-based methods such as discrete choice analysis for consumer choice making but neglect that consumers' decision-making can consist of multiple stages [9,17], especially when they face a market with a large number of alternatives to choose from. Recent researchers also started to notice the influence of consumers' social networks as peers' opinions can greatly influence individual choices [18,19]. However, it is still an emerging area for ABM-based studies to properly model the effect of consumer social networks in EV diffusion analysis.

In summary, previous ABM-based studies for EV diffusion analysis often lack considering certain important factors, such as manufacturers' launching of new products and pricing decisions, government policies and incentives, consumers' multi-stage decision-making, and the impact of consumers' social networks. Therefore, we expect to bridge these gaps and provide a more comprehensive understanding of how these factors influence the diffusion of electric vehicles.

3 Method

3.1 Overall Framework of the Proposed Approach. Figure 1 illustrates the overall framework of the proposed approach. The initial setup parameters include consumer demographics, market environment parameters, and government policies. The settings of these parameters can be obtained from survey data, government reports, or certain probabilistic distributions according to previous research. Once these parameters are loaded, the simulation works on a monthly basis (i.e., a simulation cycle). In each cycle, consumer demographics, including age and income, are updated, and new consumers are added to the market to reflect the changes in market capacity. After that, consumer social networks are constructed based on the homophily effect of consumers, e.g., consumers with similar income and residential locations are more likely to form social connections [20]. The built consumer social network will be updated along with all consumer agents' latest demographic information in each simulation cycle.

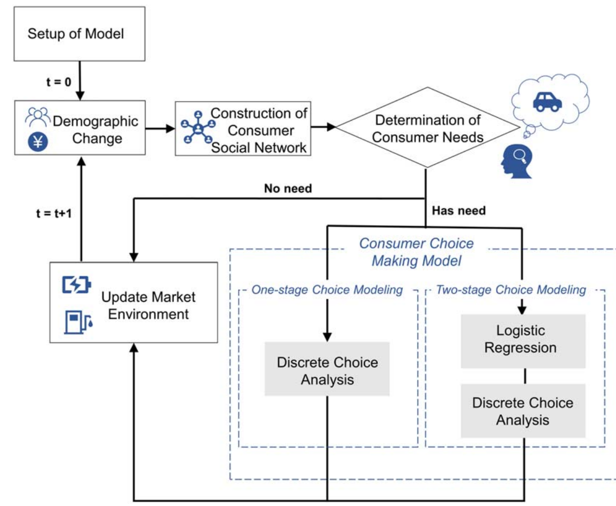

Fig. 1 The overall framework of the proposed approach

Then, each consumer evaluates whether he or she needs to purchase a new car. If there is a need, the consumer will purchase a car based on the probability of the choice making model with updated vehicle ownership information. Here, two models are available for purchase choice making. The one-stage model assumes consumers directly make a purchase choice from the entire available market, while the two-stage model assumes consumers will first decide on a small set from the market and then make the final choice. The social network of consumers will also influence their choice making by adding the utility of social influence to consumers' utility functions.

After all consumers have been updated in a cycle, the market environment is also updated, including the changes in government subsidies, restrictions on city traffic, electricity prices, and fuel prices. At the end of a cycle, the ABM model determines whether new vehicles will be introduced into the market in the next cycle. The launching of new vehicles is mainly based on the historical market data of auto companies. If there are new vehicles, they will be added to consumers' available choice options. Then, the current cycle ends, and the next cycle begins until the predetermined time is reached.

By counting the vehicles sold from one simulation cycle to another, one can infer the diffusion trend of electric vehicles in time and space. In the following subsections, the detailed settings of the proposed ABM model and key techniques for constructing the consumer choice model and consumer social network are provided.

3.2 Setup of the Model

3.2.1 Determination of the Agents and Attributes. In an ABM simulation, the first step is to determine the agents. In this study, we select consumers as the agents and designate the changes in the car market, regulation policy, electricity price, and fuel price as environmental factors. Considering consumer decision-making can be influenced by various factors, the input attributes of consumer agents include age, gender, income, residential location, work location, daily commuting distance, annual average mileage, and availability of charging infrastructure at home and work. If a consumer owns a vehicle, the brand, price, age, range, and charging time of that vehicle are also considered. These consumer data can be collected through surveys or generated randomly based on certain probabilistic distributions from previous research, while vehicle information can be sourced from the official websites of auto

Table 1 Input attributes of consumer agents and market environment in the ABM model

Attribute type	Attribute	Meaning	Value or range
Consumer attributes	a	Age	[18, 60] year
	g	Gender	{Male, Female}
	I	Income	[50,000, 500,000] CNY (Chinese Yuan)
	l	Living area	Categorical variable with 3 levels
	d_d	Daily travel distance	[0, 600] km
	d_y	Yearly travel distance	[0, 100,000] km
	c_h	Home charge	{Yes, No}
	c_w	Working place charge	{Yes, No}
Vehicle attributes	y	Car year	[0, 10] year
	e	Car engine type	{CV, PHEV, EV}
	p_c	Car price	[35,000, 1,256,000] CNY
	b	Car brand	Categorical variable with 15 levels
	r	Car range	[121, 870] km
	t	Car charging time	[0.5, 12] hour
	c_g	Gasoline consumption	[6, 12] liter/km
	c_e	Electricity consumption	[1, 4] kW·h/km
Market environment Attributes	p_g	Gasoline price	[5.69, 7.85] CNY/liter
	p_e	Electricity price	0.61 CNY/kW·h
	s	Subsidy	Categorical variable with 4 levels

manufacturers. In our model, the considered market environmental variables are prices of local fuel and electricity, which can be obtained from publicly available government reports. Table 1 shows the input attributes of consumer agents and market environment in the ABM model with their values or ranges obtained from collected questionnaires, government reports, and auto company websites. The details of these initializations are provided in Sec. 4.

To focus on the influence of consumer behaviors, we did not select the manufacturers as agents. Instead, we create a market with available vehicles for consumers to purchase based on six attributes: fuel type, price, range, fuel consumption (for PHEVs and CVs), electricity consumption (for PHEVs and EVs), as well as the time of launch into the market. This market setting is also inputted into the ABM model at the initialization process. Table 2 shows an example of a car market with five available vehicles for consumers.

3.2.2 Change of Consumer Demographics. Since consumers are getting older over time and their income usually increases with time, the demographics of consumers will be updated periodically. For consumer i, his or her age a_i and the number of years of vehicle usage y_i will change as follows:

$$a_i' = a_i + t \tag{1}$$

$$y_i' = y_i + t \tag{2}$$

where t represents the time corresponding to the length of each cycle, which can be a week, month, season, or year. Consumer income I_i will also change, and a linear growth model is applied in our study:

$$I_i' = I_i(1 + r_i) \tag{3}$$

where r_i denotes the average growth rate of income. Another way to update income is to refer to the actual monthly or yearly growth rate of salaries obtained from government statistics.

To reflect the situation of new consumers entering the market (e.g., new college graduates move to live and work here), we set the consumer agents as a dynamic group, adding 5% new consumer agents every year. Their age is set as 22 or 25 years old (corresponding to the average age of undergraduates and graduates, respectively), and their income is set based on the government's employment statistics. These new consumer agents do not own vehicles at the beginning, and their consumer attributes are randomly generated based on the probabilistic distributions of real consumer data. To simulate the influence of peers, such as the recommendations from friends when buying a car, we also construct consumers' social networks in this stage. The detailed procedures to build the network are provided in Sec. 3.4.

3.2.3 Determination of Consumer Needs. To determine whether a consumer agent has the need to purchase a new vehicle, our approach focuses on two scenarios. The first scenario is replacing old vehicles after certain years of usage. We assume consumers will need to purchase new cars when their currently owned cars exceed a certain threshold value of usage years. The second scenario is new consumers entering the market to purchase cars for working or living needs. If a consumer agent satisfies one of the scenarios above, he or she will have the need at the given timestep, and their y_i values (car year) are set to 0. The relevant attributes of the purchased vehicle model such as engine type, price, brand, range, and charging time will also be assigned.

3.2.4 Update of Market Environment. In our simulation, the market environment factors to be updated periodically are electricity and gas prices, as well as the policies on traffic control and EV

Table 2 An example of the car market with five available vehicles for consumers to choose

Vehicle ID	Engine type	Price (10,000 CNY)	Gasoline consumption (liter/100 km)	Range (km)	Electricity consumption (kW · h/km)	Time to market
1	EV	32.2	N/A	445	1.4	05/2019
2	PHEV	19.1	3.8	55	1.3	03/2021
3	PHEV	20.5	8.4	60	2.4	09/2015
4	EV	32.1	N/A	545	1.4	11/2021
5	CV	29.8	6.5	N/A	N/A	11/2008

subsidies. Since both gas and electricity prices generally exhibit an increasing trend, setting them to grow at a steady rate is adopted in our model. Consumers' energy consumption fees (c_f) will also be updated in this part. For EV and CV owners, it is easy to calculate their c_f by Eq. (4) [21]:

$$c_f = \begin{cases} p_g c_g d_d, & e = \text{CV} \\ p_e c_e d_d, & e = \text{EV} \end{cases} \tag{4}$$

where d_d is the daily travel distance, p_g is the gasoline price, c_g is the gasoline consumption, p_e is the electricity price, c_e is the electricity consumption, and e is the engine type.

For PHEV owners, we assume they will drive in electric mode until electricity is run out [21], and their c_f can be calculated as shown in Eq. (5):

$$c_f = \begin{cases} p_e c_e d_d, & e = \text{PHEV and } d_d < r \\ p_e c_e r + p_g c_g (d_d - r), & e = \text{PHEV and } d_d \geq r \end{cases} \tag{5}$$

where r is the range of PHEV.

To implement the traffic control policies, restriction areas are set in the model so that vehicles with specific attributes are not permitted to enter those areas. Subsidies, which are also an important factor influencing consumers' choices, will be updated according to governments' real policy changes. To show this effect in the model, there will be a direct discount on EVs' or PHEVs' price. In addition, the time to launch new vehicle models in the market is also considered. If the simulation time exceeds the real-time when a new vehicle model appears in the market, this particular model will be added to the available vehicles for consumers to choose.

3.3 Consumer Choice Model. Modeling consumers' purchase choices is significant in the ABM simulation of the EV market. As mentioned earlier, considering consumers in the auto market usually first decide on smaller sets of choices from the market and then make the final choices, we propose to integrate the two-stage choice model with ABM simulation to more accurately reflect consumers' decision-making process. In the first stage, we employ logistic regression to model consumers' decisions on the fuel type of vehicles, i.e., choose between conventional vehicles or non-conventional vehicles such as EVs or PHEVs. The logistic regression model [22] estimates the probability of a choice i as follows:

$$p_i = \frac{1}{1 + e^{(-z_i)}} \tag{6}$$

where z_i is the linear combination of the input variables and their corresponding coefficients, represented as

$$z_i = b_{i0} + b_{i1}x_{i1} + b_{i2}x_{i2} + \ldots + b_{in}x_{in} \tag{7}$$

Here, $\boldsymbol{x_i}$ is the vector of input variables. The coefficients $\boldsymbol{b_i}$ can be estimated using a maximum likelihood approach.

Then, in the second stage, consumers will make the final decision from a group of vehicles with the same fuel type. At this stage, we choose DCA, a classical utility theory-based model as the consumer choice model [23], which is constructed as follows:

$$U_i = V_i + \varepsilon_i \tag{8}$$

Here, U_i is the utility of the consumer choosing an alternative vehicle i, which consists of the observed utility V_i and the unobserved utility ε_i. Typically, V_i is represented in a linear additive form [23], as shown in Eq. (9):

$$V_i = \boldsymbol{x_i}\boldsymbol{\beta_i} = \beta_{i1}x_{i1} + \beta_{i2}x_{i2} + \ldots + \beta_{ik}x_{ik} \tag{9}$$

where $\boldsymbol{x_i}$ is the vector of explanatory variables (e.g., consumer demographics and vehicle attributes), and $\boldsymbol{\beta_i}$ is the vector of the coefficients quantifying consumer preferences in choice making. A commonly used form of DCA is the multinomial logit model, in which the coefficients ($\boldsymbol{\beta}$) in the observed consumer choice utility function (V) for the vehicle attributes are identical across all consumers. Equation (10) shows the calculation of the probability of the consumer's choosing a vehicle i [23]:

$$P_i = \frac{e^{x_i\beta_i}}{\sum_{j=1}^{J} e^{x_j\beta_j}} \tag{10}$$

These probabilities will eventually determine the vehicles purchased in each cycle of the ABM simulation. In our study, we examine different combinations of explanatory variables (selected from Table 1) for the DCA model and use the best combination in the simulation of ABM. The two-stage choice modeling can reflect consumers' decision process in purchasing vehicles more accurately. As a comparison, we also develop the one-stage choice model, which adopts similar utility function forms as shown in Eqs. (8) and (9) but the alternatives for consumers to choose become the whole available vehicles from the market.

3.4 Social Network of Consumers. To model the social influence between consumers in our simulation, we construct a social network of consumers based on the homophily effect of consumers' residential distance and income, i.e., consumers who live close to and earn similar income tend to form links in a social network. The primary impact of social networks on the ABM model is that if two consumer agents are linked, one agent's evaluation of the car will affect another agent's utility in choosing that car. This is also referred as to the WOM effect, which can be expressed in Eq. (11):

$$U_i' = U_i + U_{w,i} \tag{11}$$

where $U_{w,i}$ is the WOM component. According to previous research [15,24], it can be calculated as

$$U_{w,i} = n_{w,i}\gamma(n_{w,i})\phi \tag{12}$$

where $n_{w,i}$ denotes the number of positive comments a consumer receives from his/her social connections that own the vehicle i. ϕ is the consumer's sensitivity to the WOM effect. $\gamma(n_{w,i})$ is a decreasing cascade model, as shown in Eq. (13) [25], in which more recommenders will lower their respective influencing power.

$$\gamma(n_{w,i}) = \left(\frac{1 + ln(n + 0.25)}{n + 0.15}\right)^{\zeta} \tag{13}$$

where ζ is a power parameter that controls the real sales data and can be found by Monte Carlo simulations to find the best value to fit the real data, and n is the number of recommenders.

4 Case Study

To validate the proposed approach, we present a case study employing the survey data collected from Shanghai, China, to simulate the change in the auto market. The collected information includes car owners' age, gender, residential and workplace location, vehicle ownership and related vehicle information, vehicle purchase considerations and preferences, charging capabilities, and usage habits such as daily or yearly driving distance. A total of 1500 car owners' responses were collected, of which 1463 were deemed valid. Among the valid responses, 724 respondents reported owning non-conventional vehicles, while 739 reported owning conventional vehicles. This dataset is used as the input for the consumer choice model and the initialization settings of the ABM. We implement the ABM using NetLogo[2] [26], which can visualize the changes in the market intuitively. The

[2]Researchers can send emails to xujiawen@sjtu.edu.cn to request access to the model and raw data.

Table 3 The best combination of explanatory variables in the consumer choice model with their respective importance to consumers' purchase decisions

Variables	Importance
Car price	21.41%
Car range	16.81%
Income	14.62%
Availability of home charge	13.50%
Daily travel distance	12.11%
Engine type	11.34%
Horse power	6.03%
Yearly travel distance	4.18%

estimation of coefficients for the consumer choice models, including both DCA and logistic regression, are implemented in R.

In the setting of the ABM parameters, most of the consumer attributes listed in Table 1 take their initial values from the collected questionnaires except consumers' income increasing rate, which refers to the government report [27]. For new consumer agents entering the market, we create these agents according to the distribution of real consumer attribute data collected. Most vehicle attributes are obtained from a popular auto online forum in China,[3] while the threshold year for car change is set according to the government report [28]. As for the market environment attributes, the gasoline price is obtained from a public report [29], and the electricity price (0.61 CNY/kW·h) originates from the national power company in China [30]. The EV subsidy data come from government agencies [31–33], and these subsidies are decreasing year by year. Table 1 shows the range or value of these attributes.

To make our model align better with the real market, we have undertaken a significant amount of tuning work, primarily involving data collection, selection of model and modeling variables, and model training and validation. Take the construction of the consumer choice model in the ABM as an example. To align user preferences more closely with the electric vehicle market in Shanghai, we first collected user information and vehicle market data from questionnaires and auto company websites. Considering the need of modeling users' purchasing intentions, we opted for the classic DCA model as the main consumer choice model. Based on previous research and preliminary tests, car price, car range, income, availability of home charge, daily travel distance, engine type, horsepower, and yearly travel distance are selected as the modeling variables in DCA. Their respective importance is provided in Table 3.

In our ABM model, some of the processes are stochastic in nature. For instance, the purchase choice made by each consumer is based on the probability distribution of the consumer's utility for a car. Additionally, the installation of charging stations at home and workplace, as well as the distribution of city population, is also stochastic, which introduces randomness into the modeling process. For modeling processes with a high degree of determinism, such as regional population distribution proportions, we cross-referenced survey data with credible publicly available government reports and input these parameters into the model. To ensure the model's long-term effectiveness, the constructed ABM model should be periodically updated with the most recent data, ensuring it adapts to the changing circumstances over time.

5 Results

In this section, we first present the simulation results of the proposed ABM model and then compare it with two ablation models and traditional statistical models. We also show the what-if scenario tests and discuss how government policy changes and technological improvements will influence the diffusion of EVs.

[3]http://www.autohome.com.cn/.

5.1 The Simulation Results of the Proposed Agent-Based Modeling Model. Figure 2 shows the visualized simulation results of the proposed ABM model in 3 years with a starting of 5000 consumer agents. The black, red, and green agents represent owners of CV, PHEV, and EV, respectively. The red circle represents the inner ring of Shanghai, which is the city center area with congested traffic. The green circle represents the outer ring of Shanghai, meaning the regions outside that ring are normally considered as suburbs. People living in different areas have different average commute distances, which will greatly influence their choice making. An important regulation policy in Shanghai is that CV owners must purchase license plates (its price is around 90 thousand Chinese yuan or 13 thousand US dollars in 2022) to drive freely inside the outer ring area, while EV and PHEV owners can get this license plate freely (this benefit for PHEV owners ended in 2023). As shown in Fig. 2, at the beginning of the simulation, the majority of the market were CV owners (80% of agents owned conventional vehicles in 2016). However, the market share of EVs and PHEVs gradually increased until 2020, when consumers holding CVs accounted for 60% in 2020.

Our simulation begins at the beginning of January 2016 (time-step = 0) and ends up at the end of December 2020 (time-step = 59). Figure 3 provides the sales volumes of EVs (green), PHEVs (blue), and CVs (yellow) from 2016 to 2020. It can be observed that from 2016 to 2019, the sales of EVs and PHEVs have been increasing year by year since the growth rate of the whole market size cannot match with the increase in EV and PHEV sales. From 2019 to 2020, the sales of EVs almost stay the same. One possible reason is that there was a large decrease in government subsidies for EVs and PHEVs in 2020 [24]. On the other hand, the sales of CVs have been decreasing year by year. Although the growth rate of EV sales is higher compared to PHEV sales, the actual number of PHEV sales is still greater than EV sales.

Figure 4 shows the comparison of market share obtained from the simulation results of our proposed ABM model (without slant lines) and the real market data collected from the government report (with slant lines). Our simulation results match well with the real market variations that PHEVs' and EVs' market share grew rapidly from 2016 to 2019. Due to the shrinkage of government subsidies in 2020, the market share of EVs almost stayed the same from 2019 to 2020, while the market share of PHEVs grew a little. These results indicate the validity of our proposed approach.

5.2 Benchmark Analysis of the Proposed Agent-Based Modeling Model. In order to examine the performance of the proposed ABM model, we compare various benchmark models' forecasts for car sales in 2020. Due to the limited dataset, learning-based models such as long short-term memory networks and graph neural networks are not included in this comparison since they require large-scale datasets for model training. Instead, we choose to compare our model with two ablation models (one removes the two-stage choice model, and the other removes the social network of consumers from the proposed model) and two traditional statistical models, linear regression and autoregressive integrated moving average (ARIMA). For the two statistical models, we use the real sales data of EV, PHEV, and CV in Shanghai from January 2016 to December 2019 (48 months) as the training dataset and forecast the sales for the following 12 months. Then, the proportions of the predicted EV, PHEV, and CV sales from these models are calculated, as shown in Table 4.

From Table 4, it is evident that the proposed model is more accurate in predicting the proportions of CV, PHEV, and EV sales. In addition, the proposed model is better at predicting the ratio of the proportions of new energy vehicles (i.e., PHEVs plus EVs) and CVs. The proposed model without the two-stage choice model is slightly inferior as it fails to simulate consumers' decision-making process in choosing the fuel type before selecting a specific vehicle model, which may result in some bias. The proposed model without the consumer social network and the linear regression

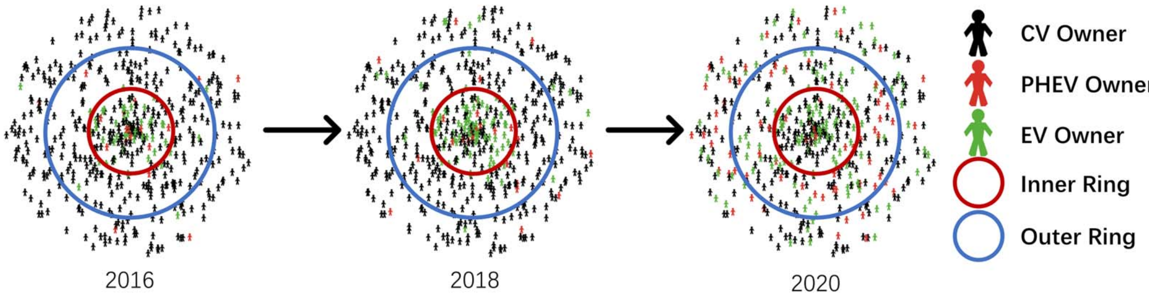

Fig. 2 The visualization of the simulation results of the proposed ABM model in 3 years. Here, we only show 500 agents for a clear view. The actual simulation involves 5000 agents at the beginning.

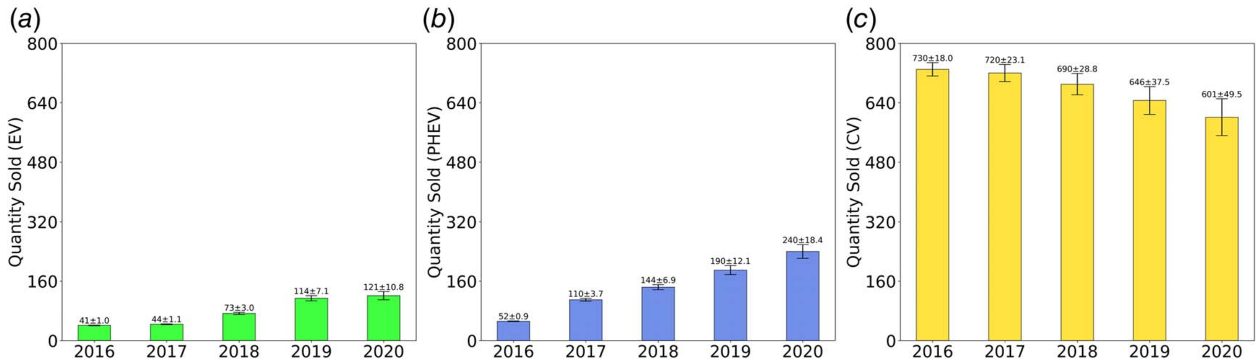

Fig. 3 Simulated quantity of sold (*a*) EV, (*b*) PHEV, and (*c*) CV obtained from the proposed ABM model

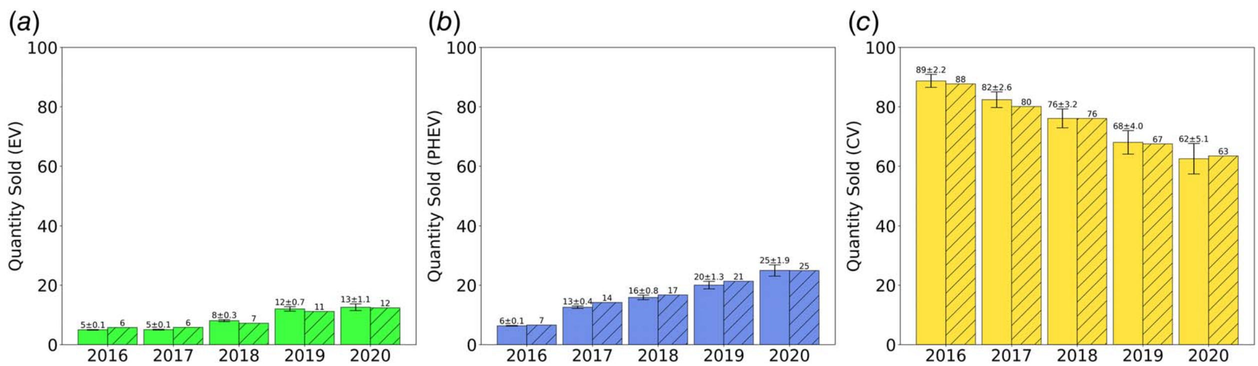

Fig. 4 Comparison of market share obtained from the proposed ABM model (without slanted lines) and real market data (with slanted lines) for (*a*) EV, (*b*) PHEV, and (*c*) CV

model show significant deviations in predicting EV and PHEV sales due to their inability to simulate the spreading effect of the social network of EV/PHEV users. In our study, only 48 months of data are available for model training, making it challenging for ARIMA to capture the complex long-term patterns and predict the future 12 months accurately.

5.3 What-If Scenario Tests. In the following subsections, we present the results of what-if scenario tests to examine the impact of changes in the market environment, government policy, consumer demographics, and vehicle design on the market share of EVs.

5.3.1 Change of Market Environment and Government Policy. In this scenario, we assume the gas price doubled at the beginning of 2018 and remained at that level for the next few years. Figure 5 shows the comparison of market share between the proposed model (without slant lines) and the model with doubled gas price (with slant lines). We can see that after 2018, the sales of EV and CV have both increased. The doubling of gas prices over three years has resulted in 2.5% and 2.8% increase in the market share of EVs and PHEVs, respectively. One possible reason is that the doubling of gas prices increases the expected long-term usage cost for CV owners, leading them to be more inclined to purchase EVs or PHEVs when replacing their current vehicles.

Figure 6 shows the comparison of market share between the proposed model (without slant lines) and the model without subsidies for EVs and PHEVs (with slant lines). Here, we assume the government did not promote new energy vehicles, i.e., there were no subsidy policies from the beginning of the simulation. We can see that in this case, the sales of EVs and PHEVs would be much smaller in the initial stage of entering the market, and their growth would be much slower. One possible explanation is that subsidies directly affect the price of EVs and PHEVs, which exhibits a high importance to consumers' purchase decisions according to the results in Table 3. Thus, it has a significant impact on the market share of EVs.

5.3.2 Change of Consumers. In this scenario, we examine whether a static market would affect the simulation results. A

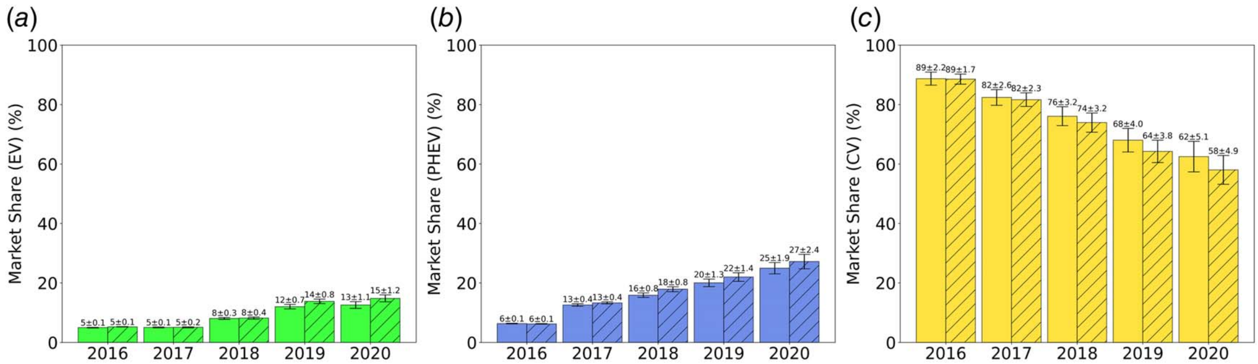

Fig. 5 Comparison of (*a*) EV, (*b*) PHEV, and (*c*) CV's market share between the proposed model (without slanted lines) and the model with doubled gasoline price (with slanted lines)

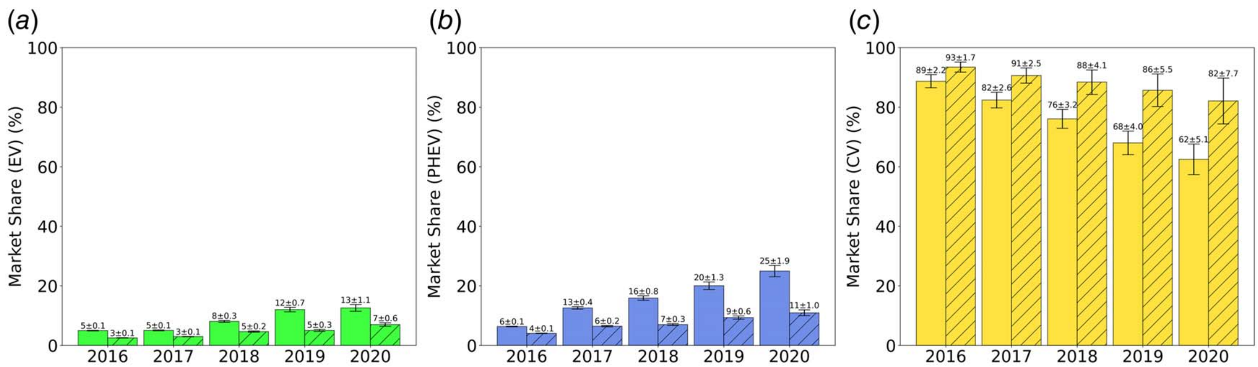

Fig. 6 Comparison of (*a*) EV, (*b*) PHEV, and (*c*) CV's market share between the proposed model (without slanted lines) and the model without subsidies for EVs and PHEVs (with slanted lines)

Table 4 Comparison of the predicted 2020 annual market share of EV, PHEV, and CV obtained from the proposed ABM model and four benchmark models

	EV	PHEV	CV	(EV + PHEV)/CV
Real market data	12.39%	24.19%	63.42%	57.68%
Proposed model	12.58%	24.94%	62.47%	60.06%
Proposed model without two-stage	13.26%	25.38%	61.36%	62.97%
Proposed model without network	10.15%	18.42%	71.38%	40.10%
ARIMA	14.23%	21.43%	64.33%	55.45%
Linear regression	11.24%	19.54%	69.22%	44.47%

static market means no new consumers enter the market, and the market size remains the same all the time. Figure 7 shows the comparison of market share between the proposed model (without slant lines) and the model with static consumer agents (with slant lines). We can see that in the static market scenario, the market share of PHEVs and EVs has decreased. One possible explanation is that young consumers are often more receptive to new technologies, while in a static market, no young consumers will be added.

5.3.3 Change of Automotive Manufacturers. In this scenario, we assume that the range of all EVs in the market has increased by 20%. Figure 8 shows the comparison of market share between the proposed model (without slant lines) and the model with increased range EVs (with slant lines). We can see that after the

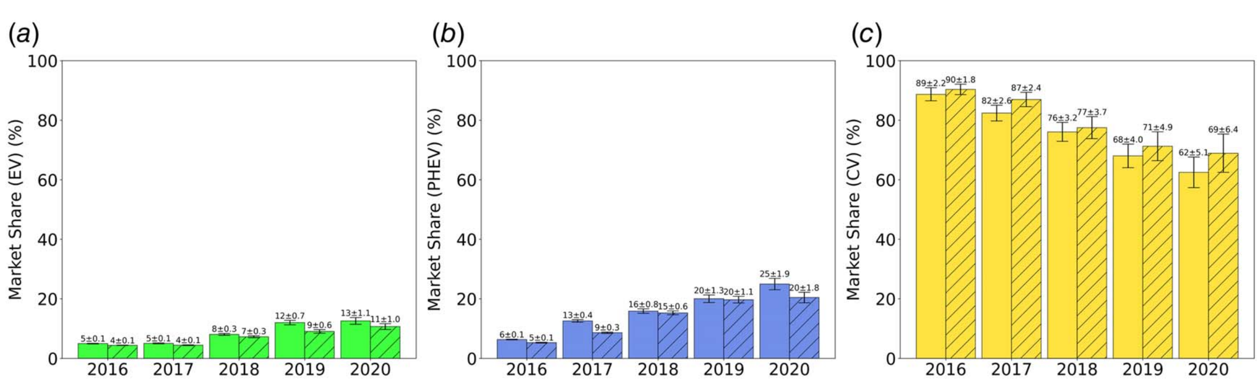

Fig. 7 Comparison of (*a*) EV, (*b*) PHEV, and (*c*) CV's market share between the proposed model (without slanted lines) and the model with static number of consumer agents (with slanted lines)

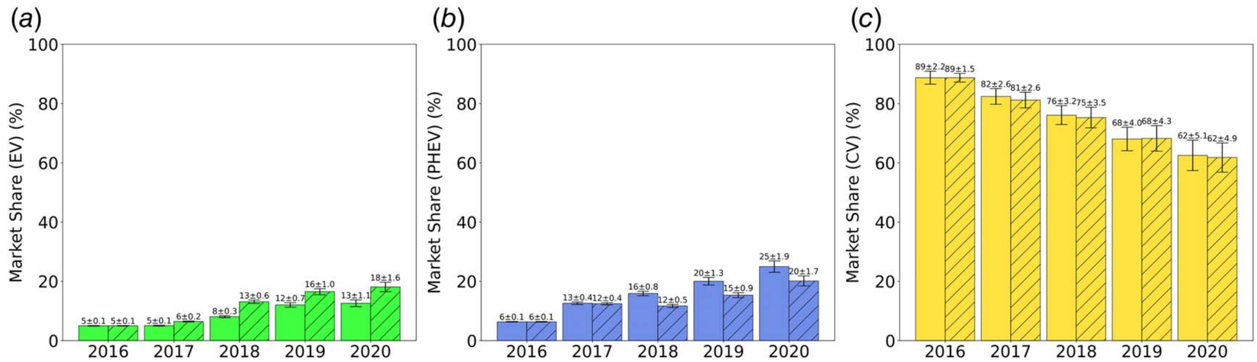

Fig. 8 Comparison of (*a*) EV, (*b*) PHEV, and (*c*) CV's market share between the proposed model (without slanted lines) and the model with increased range EVs (with slanted lines)

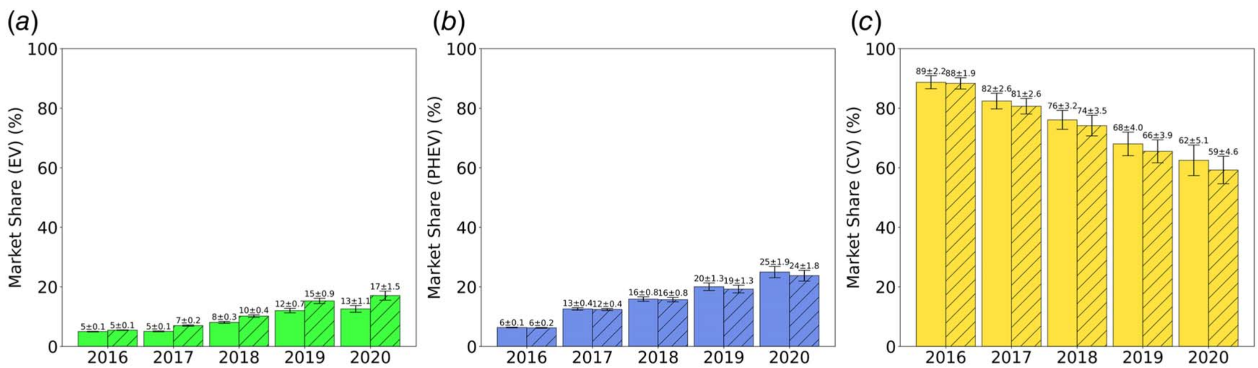

Fig. 9 Comparison of (*a*) EV, (*b*) PHEV, and (*c*) CV's market share between the proposed model (without slanted lines) and the model with shorter-charging-time EVs and PHEVs (with slanted lines)

increase in the EV range, although the market share of CVs has hardly changed (decreased by less than 1%), the sales of EVs has increased significantly, and the sales of PHEVs has decreased noticeably. In 2020, the market share of EVs increased from 17% in the proposed model to 20% in the compared scenario, and the market share of PHEVs decreased correspondingly. This is an interesting observation since the market share of CVs was not affected by the increase in the EV range. One possible explanation is that consumers usually first decide whether to purchase a CV or a new energy vehicle at the beginning, in which range may not be considered during this initial decision-making process. Only after they have decided to purchase a new energy vehicle, will the increase in EV range lead to an increase in EV sales.

Similarly, we test another scenario where the charging time for EVs and PHEVs is reduced by half. The charging time for EVs in the market was 6–8 h in 2016 and 2–3 h in 2020, which is reduced to 3–4 h in 2016 and 1–1.5 h in 2020 in the testing scenario. For PHEVs, the original 1–4-h charging time is reduced to 0.5–2 h. Figure 9 shows the comparison of market share between the proposed model (without slant lines) and the model with shorter-charging-time EVs and PHEVs (with slant lines). We can see that after the charging time is shortened, the sales of EVs has increased significantly, while the sales of PHEVs remains relatively stable. From this result, we infer that consumers who purchase PHEVs may not be too troubled by charging. If they have no access to charging, they will choose to refuel gasoline quickly to continue driving. On the other hand, charging time is critical for EV owners, and reducing it can alleviate the range anxiety greatly.

6 Conclusion

In this technical brief, we present an agent-based modeling approach for the diffusion analysis of electric vehicles with two-stage choice modeling. In addition, consumers' social networks built on the homophily effect of consumers' income and residential locations are also considered in the ABM simulation to reflect the impact of the WOM effect on consumers' purchase decisions. These treatments further improve the accuracy of the diffusion analysis of electric vehicles. Using data collected from Shanghai, China, we simulate the diffusion of EVs in Shanghai's auto market and validate the effectiveness of the proposed approach. We compare the proposed approach with two ablation models and traditional statistical models and find the simulated diffusion of EVs provided by the proposed model is closer to the real market dynamics, particularly in determining the market share of new energy vehicles.

In our study, we also examine the influence of gas price, EV subsidies, consumer demographics, and range and charging time of EVs on the diffusion of EVs through what-if scenario tests. Our tests show that subsidies have a significant impact on the sales of EVs and PHEVs. A substantial increase in gas price would reduce the CV market while increasing the market for new energy vehicles, but would not affect the ratio between the sales of EVs and PHEVs. A sudden increase in the range of EVs and a decrease in their charging time would promote EV sales and reduce CV sales but have a relatively small impact on PHEV sales. These insights can assist automakers in improving their design of next-generation products and enhancing their market competitiveness.

Although this technical brief uses the auto market in Shanghai as a demonstration, the proposed approach can be applied as well to the diffusion analysis of other auto markets as long as the corresponding consumer and market data are available. One limitation of this work is that our approach underestimates the effect of the subsidy shrink, which leads to a small deviation of the predicted market share of new energy vehicles from the real market data. Future work includes a more thorough investigation of the factors affecting consumer behaviors and the potential impact of policy changes on the EV market.

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Funding Data

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Conflict of Interest

There are no conflicts of interest.

Data Availability Statement

The datasets generated and supporting the findings of this article are obtainable from the corresponding author upon reasonable request.

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