Agent-based modeling of electric vehicle diffusion under the phase-out of charging infrastructure subsidies in China

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ABSTRACT

Government subsidies for electric vehicle charging infrastructure (EVCI) in China have accelerated the deployment of charging stations and promoted the diffusion of electric vehicles (EVs). However, these subsidies have also imposed a substantial fiscal burden on public finances. While much of the existing literature compares different types of EVCI subsidies, few studies explore the implications of phasing out EVCI-related subsidies for government spending and EV diffusion. This paper develops an agent-based model (ABM) incorporating EVCI operator, heterogeneous EV consumers, and the government to analyze how EVCI subsidies influence EV diffusion and proposes tailored phase-out policy combinations. A key innovation of this study is the integration of private charging pile-related factors into the consumer decision-making process through a discrete choice experiment. Additionally, regional disparities in EV diffusion between urban and suburban areas under EVCI subsidies are explored, and we find that by 2030, the EV penetration rate could reach 79.78 %, with suburban EV ownership surpassing that of urban areas. While EVCI subsidies significantly influence early and mid-stage EV adoption, their effectiveness diminishes in the later stages. Implementing phase-out subsidies under current standards can reduce cumulative government spending by approximately 91 % compared to a no-phase-out scenario, with only a marginal decline of 0.05 % in EV ownership. A comparative analysis of 50 subsidy phase-out policy combinations reveals that those featuring high initial operating subsidies with low initial construction subsidies under a rapid phase-out mode are the most cost-effective. The policy recommendations proposed alleviate fiscal burdens and promote more balanced EV development between urban and suburban areas.

1. Introduction

Under the dual objectives of carbon peaking and carbon neutrality, accelerating the electrification of the transportation sector has become a key pathway for China to fulfill its emission reduction commitments (Bao et al., 2023; Zhong et al., 2024). Within this electrification agenda, the electric vehicle (EV) industry has experienced rapid growth, largely driven by supportive government subsidies. By the end of 2024, the number of EVs in China had reached 31.4 million (Kong, 2025). However, the development of electric vehicle charging infrastructure (EVCI)

to support EV adoption remains hindered by significant imbalances. The first challenge is a quantity imbalance. By the end of 2024, China had installed approximately 3.579 million public charging piles (PCPs) and 9.239 million private charging piles (PrCPs).[1] With an EV fleet of 31.4 million, the resulting vehicle-to-charging pile ratio is roughly 2.45:1, which falls below the targeted 1:1 ratio (National Development and Reform Commission [NDRC], 2015). The second challenge is spatial distribution imbalance (Y. Shang et al., 2025). EVCI deployment in China shows a clear regional disparity, with higher densities generally observed in the south than the north and broader coverage in the east

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relative to the west.[2] In major cities, the average EVCI coverage rate in central urban areas reaches 80.8 %, compared with less than 5.0 % in rural areas.[3] EVCI plays a crucial role in alleviating range anxiety among EV users and is widely recognized as a critical influential factor of EV adoption (X. Li and Liu, 2023; Z. Wang, 2020). The effect of EVCI deployment on EV adoption can be explained through the lens of indirect network effect (INE), which refers to the phenomenon in which a user's utility from adopting a particular product increases with the adoption of a complementary product (Katz and Shapiro, 1985). In the EV market, EVCI serves as a complementary good to EVs, and its quantity has an indirect yet substantial impact on the user experience of EV owners (Sun et al., 2018). Limited access to EVCI remains a major obstacle to EV adoption (Y. Liu et al., 2015).

Since 2015, the Chinese government has implemented a series of subsidy policies for EVCI operators to accelerate the development of charging infrastructure (W. Shang et al., 2024). In the preliminary stages, these efforts primarily targeted charging station construction subsidies (CSs), aimed at alleviating the initial investment burden on operators and thereby stimulating the expansion of charging networks. Beginning in 2016, the government implemented operational subsidies (OSs) to incentivize greater efficiency among charging station operators, and under this policy, operators receive subsidies based on the actual volume of electricity dispensed. However, the extensive EVCI subsidies have imposed a growing fiscal burden on the governments. According to reports from the Ministry of Finance of the P.R.C.,[4] cumulative subsidies for EVCI amounted to 7.556 billion RMB between 2016 and 2020. In response, several regions (provinces) in China have begun adjusting their subsidy policies. For example, Hunan and Hainan Provinces have adopted phased reduction policies for EVCI subsidies, gradually lowering the subsidy levels on an annual basis.[5] To date, limited attention has been given to the reduction of EVCI subsidies and their potential consequences. Moreover, most existing research has predominantly focused on PCPs, with few studies investigating the role of PrCPs in EV diffusion. In reality, PCPs account for only 27.92 % of China's total EVCI stock,[6] and the ability of EV users to install PrCPs is another critical factor influencing purchase decisions (Qian et al., 2019). Therefore, incorporating the role of PrCPs into studies of EV diffusion is essential to more accurately reflect real-world EV adoption patterns.

In addition to incentive policies and EVCI, the diffusion of EVs is shaped by other factors such as vehicle attributes, fuel prices, and individual income levels (Su and Diao, 2025). Accordingly, the EV diffusion process can be conceptualized as a complex system in which agents, such as consumers, operators, and policymakers, interact with each other over time within a dynamic environment. Agent-based modeling (ABM) approach provides a robust framework for analyzing such systems. By constructing micro-level agents with heterogeneous attributes and decision-making rules, ABM allows for autonomous decision-making and interactions within a defined environment, thereby enabling the exploration of diffusion pathways over time (Mehdizadeh

et al., 2022). Building on this, this study develops an ABM framework incorporating heterogeneous EV consumers, EVCI operator, and the government to examine the impacts of EVCI incentive policies on the diffusion of EVs. The main contributions of this study are as follows: First, it examines the impact of EVCI subsidy phase-out on both EV diffusion and government fiscal expenditure, while also conducting a comparative analysis of alternative phase-out strategies. To the best of our knowledge, it represents the first quantitative evaluation of different EVCI subsidy withdrawal scenarios, which thereby offers valuable policy insights for the design of the phased subsidy reduction. Second, this study examines the spatial distribution of EVCI by comparing the diffusion patterns of EVs and charging piles in urban versus suburban areas and identifies effective policy strategies to address persistent imbalances in EVCI deployment across different geographic regions. Third, this study examines the role of PrCPs in consumer EV purchase decisions by integrating PrCPs installation into the decision-making process within an ABM framework and further simulates the diffusion of PrCPs, which addresses a notable gap in the existing literature on private charging infrastructure.

The remainder of this paper is organized as follows: Section 2 reviews the relevant literature on EVCI subsidies and EV diffusion modeling. Section 3 outlines the ABM framework. Section 4 details the parameter settings and model validation. Section 5 presents simulation results and conducts sensitivity analysis. Finally, Section 6 concludes with the main findings.

2. Literature review

2.1. EV and EVCI policies

The rapid expansion of EVs in the Chinese market has been largely driven by strong policy support. To encourage EV adoption, the government has primarily relied on a series of policies such as license plate restrictions, EV purchase tax exemptions, and EV purchase subsidies. The effectiveness of these policy instruments has been extensively documented in the existing literature (Shen et al., 2021; Sun et al., 2018; T. Zhang et al., 2024). While license plate control policies can strongly influence EV adoption, their impact is geographically restricted as they are implemented in only a limited number of cities. By contrast, purchase tax exemptions and purchase subsidies are applied more broadly and play a more important role on EV diffusion (Zhu et al., 2022). However, with the rapid expansion of the EV market and growing fiscal pressures, direct purchase subsidies were gradually reduced and ultimately phased out by the end of 2022.

Given the phase-out of EV purchase subsidies, scholars have increasingly shifted their attention to EVCI subsidy policies. Li et al. (2017) identified a feedback loop between EV adoption and charging infrastructure deployment. Their findings indicate that, ceteris paribus, CSs for EVCI have twice the effect on EV diffusion as EV purchase subsidies. Zhu et al. (2019) argued that, in the context of EV purchase subsidy withdrawal, the government should increase CSs for EVCI to sustain EV market growth. Zhang et al. (2024) examined the effects of different subsidy combinations, including EV purchase subsidies and EVCI CSs, on EV sales. Their findings suggest that, as the EV market matures, purchase subsidies should be gradually redirected toward supporting EVCI construction, with CSs progressively phased out in the later stages of market development. Following the introduction of OSs for charging stations, some scholars have examined the combined effects of CSs and OSs on EVCI development and diffusion. Luo et al. (2023) assessed the effectiveness of different subsidy types in EV adoption and found that the cost of acquiring one additional EV user through EV purchase subsidies is much higher than through either CSs or OSs. Ling et al. (2024) analyzed how different combinations of CSs and OSs affect the decision-making of EVCI operators and concluded that CSs are more suitable for operators with low operating cost coefficients (which measure the operational capability, with lower values indicating lower costs

to achieve the same level of service), whereas OSs are more effective for those with relatively high cost coefficients. Chen et al. (2023) found that the marginal effects of investment subsidies, CSs, and OSs on EVCI deployment differ, with investment subsidies exhibiting the most pronounced diminishing marginal effect.

In summary, with the withdrawal of EV purchase subsidies and the implementation of charging station subsidies in China, scholars have increasingly focused on the impact of these policy shifts. However, few studies have analyzed CSs and OSs within an integrated analytical framework, and even fewer have quantitatively assessed the consequences of EVCI subsidy phase-outs. As with EV purchase subsidies, the subsidies for charging stations are also expected to be gradually phased out as the EVCI industry matures. It is therefore essential to design optimized phase-out strategies that reduce fiscal expenditure while minimizing potential adverse effects on EV development.

2.2. Indirect network effects

The influence of charging infrastructure on EV diffusion can be understood through the lens of INE. First introduced by Katz and Shapiro (1985), INE describes situations in which the utility a consumer derives from a product is correlated with the availability of a complementary product. The existence and significance of INE have been confirmed across various industries, such as video games (Clements and Ohashi, 2005), DVDs (Inceoglu and Park, 2011), and television sets (X. Zhang, 2007). In recent years, numerous studies have examined the INE between EVs and EVCI, which can generally be classified into macro-level and micro-level analyses. Macro-level studies primarily assess the impact of EVCI quantity on EV adoption using aggregate data. Drawing on data from China's EV market, Li and Liu (2023) demonstrated the positive impacts of EVCI on EV diffusion in terms of both EVCI stocks and density. Based on data from the U.S. market, Li et al. (2017) further confirmed the significant influence of INE on EV diffusion through an empirical study. Similarly, Koch et al. (2022) analyzed the INE in the Norwegian EV market by constructing an econometric model and found that its intensity is lower than in the United States.

Micro-level studies, by contrast, focus on how the quantity of EVCI in a user's vicinity affects perceived utility, typically relying on questionnaires to capture user preferences. Sun et al. (2018a,b), for example, conducted a discrete choice experiment with individual-level data and found that INE positively influences EV choice, with their heterogeneity analysis further revealing substantial variation in sensitivity to INE across different user groups. Likewise, Liu et al. (2015) confirmed the presence of INE in the EV market using questionnaire data and noted that EVCI-related INE issues hinder EV purchases. Overall, the existence and importance of INE are well established in previous research. Building on this foundation, our study incorporates INE into an ABM framework to simulate the dynamic relationships between the diffusion of EVs and EVCI.

2.3. EV diffusion research methodologies

A substantial body of research has explored EV diffusion through methodologies such as the Bass model, system dynamics (SD), and ABM. The Bass model, originally proposed by Bass (1969), is widely used to quantify innovation diffusion processes and has been applied by several scholars to analyze EV adoption. For instance, Shi et al. (2022) developed a Bass model incorporating vehicle scrappage and internal combustion engine vehicle (ICEV) competition mechanisms to predict EV diffusion in Shanghai under policy influences. Yang et al. (2025) integrated uncertainty theory into the Bass model to simulate EV sales growth under disruptive events, while Fan et al. (2025) proposed a Bass model with a green premium factor to forecast EV sales in the Chinese market. Nevertheless, although the Bass model is relatively simple and data-efficient, its inability to account for external influential factors has limited its applicability to the early stages of EV diffusion research.

Unlike the Bass model, SD allows for the incorporation of a wider range of influencing factors from a macro-level perspective. Li et al. (2023) developed an SD-based EV diffusion model to analyze the impacts of factors such as vehicle performance and charging convenience. Similarly, Zhu et al. (2024) constructed an EV diffusion model incorporating vehicle performance, EVCI, and policy factors, which enabled a comparative analysis of different policy measures in promoting EV diffusion. Using an SD framework that involves government, firms, and consumers, Kong et al. (2020) assessed the effects of phasing out EV purchase subsidies on EV market share. Shen et al. (2021) analyzed the impact of subsidy phase-out policies in Shanghai on local EV adoption, and similarly, Kim et al. (2021) projected EV diffusion trends in South Korean cities through an SD approach and evaluated the effectiveness of subsidy policies on EV penetration.

However, neither the Bass model nor SD is capable of explicitly capturing the impact of individual-level behavior on the overall system. In contrast, the ABM approach enables the construction of multiple heterogeneous agents within a studied environment. These agents interact with each other and with their environment, thereby generating complex phenomena and patterns at the macro level (Mehdizadeh et al., 2022). Consequently, a growing number of scholars have studied EV adoption with the ABM approach. For example, Eppstein et al. (2011) developed a micro-level ABM of EV diffusion that incorporates agent behaviors shaped by media information dissemination and peer effects. Zhang et al. (2011) combined the multinomial logit model with an ABM framework to represent heterogeneous consumers based on empirical data. Other scholars have further leveraged ABM's capabilities to analyze how social relationships among users influence overall EV development (Shafiei et al., 2012; Xu and Bi, 2024). Table 1 below summarizes the literature employing the aforementioned methods to study EV adoption.

Besides, several scholars have also leveraged the spatial modeling capabilities of ABM to explore the spatial diffusion of EVs and EVCI and to forecast their spread across geographical regions. Wang et al. (2023) modeled the spatial development of the EV market from 2015 to 2040 and found that EV users gradually form clusters over time. Silvia and Krause (2016) divided an urban area into commercial and residential zones, allocating PCPs in varying quantities across these zones to reflect a realistic charging network structure. Similarly, Huétink et al. (2010) adopted a spatial segmentation approach and divided the study region into urban and rural areas to analyze how different hydrogen refueling infrastructure deployment strategies influence the diffusion of hydrogen vehicles. Moreover, by integrating ABM with geographic information systems (GISs), some researchers have developed spatial environments that reflect urban characteristics, thereby enabling more accurate analyses of EV and EVCI diffusion within specific city contexts (Luo et al., 2023; Zhuge et al., 2021). Although these studies leverage ABM's spatial modeling capabilities to segment the simulation space, the demographic characteristics assigned to different regions often rely on subjective assumptions rather than empirical evidence. Table 2 summarizes the relevant literature on EV diffusion with an ABM approach.

This paper seeks to simulate the diffusion of EVs and charging stations under real-world conditions by incorporating individualized factors such as consumer location, the number of nearby PCSs, and the feasibility of installing PrCPs. The ABM approach, characterized by its bottom-up framework for modeling individual behavior to derive system-level outcomes, is particularly suited for simulating EV diffusion under heterogeneous consumer preferences. Moreover, by utilizing spatial modeling capabilities, this study analyzes the spatial dynamics of EV diffusion and proposes differentiated strategies for promoting EV uptake in urban and suburban areas based on the simulation results.

Table 1
Overview of literature on EV adoption.

Methodology	Reference	Main content	Summary
Bass model	Shi et al. (2022) X. Yang et al. (2025) Fan et al. (2025)	A Bass model incorporating vehicle scrappage and technological competition to analyze EV diffusion in Shanghai, China. Integration of uncertainty theory with the Bass model to analyze EV diffusion under the influence of uncertain events. A Bass model incorporating the green premium of EVs.	Although the Bass model offers advantages such as relative simplicity and low data requirements, its applicability is constrained by limited flexibility in capturing the influence of external environmental factors.
System dynamics (SD)	Y. Li et al. (2023) Shen et al. (2021) Zhu et al. (2024) Kong et al. (2020) Kim et al. (2021)	A multi-agent interaction SD model to analyze the impacts of different subsidy schemes on EV diffusion and carbon emissions. An SD model considering dynamic technological maturity evolution and incentive phase-out. An SD model incorporating multi-agent interactions based on INE to compare the effectiveness of different policies in promoting EV diffusion. An SD model of EV diffusion incorporating interactions among the government, firms, and consumers. An SD model of EV diffusion incorporating policy incentives and environmental benefits.	SD can capture interactions among heterogeneous agents and allows for a simulation of feedback in complex systems. However, it faces limitations in explicitly representing system-level phenomena that arise from individual responses to external factors.
Agent-based modeling (ABM)	Zhang et al. (2011) Eppstein et al. (2011) Shafiei et al. (2012) Xu and Bi (2024) Sun et al. (2018) Y. Wang et al. (2023) Luo et al. (2023) Zhuge et al. (2021)	An ABM exploring the impact of exogenous factors on EV adoption in the context of multi-agent interactions between manufacturers, consumers, and the government. An ABM investigating the nonlinear impact of social influence and media exposure on EV market penetration. An ABM forecasting EV adoption through perceived utility and social influence within a choice-based diffusion framework. An ABM considering the impact of word-of-mouth effects and social networks on consumers' decisions to purchase EVs. An INE-based ABM evaluating the influence of spatial EVCI deployment policies on EV diffusion. An INE-based ABM evaluating the impact of the government and operator EVCI deployment on EV diffusion. An ABM modeling the role of policy and external factors in overcoming the EV diffusion bottleneck. A GIS-based ABM evaluating the impacts of EV price, range, and EVCI on EV diffusion across different regions in Beijing, China.	ABM can capture complex interactions among heterogeneous agents and between agents and their environment at a macro level.

3. Methodology

3.1. Agent-based modeling description

This paper constructs a multi-agent system within an ABM framework, incorporating EV consumers, EVCI operator, and the government, to evaluate the impacts of policy interventions on the EV market. As vehicle performance and charging infrastructure continue to evolve, potential consumers may shift their preferences from ICEVs to EVs, thereby reshaping overall charging demand. In response to this changing demand and government subsidy policies, EVCI operator adjusts its PCS deployment strategies, which in turn further influence the development of the charging environment. Furthermore, considering the influence of PrCPs on consumer purchase decisions and the differences in installation conditions between urban and suburban areas in China, this paper adopts an urban-suburban classification to capture regional heterogeneity. Sub-models for each agent are described in detail in the following sections.

3.2. Consumer sub-model

The ABM framework centers on the decision-making behavior of consumers, assuming that they follow a utility maximization approach that accounts for vehicle attributes, charging station characteristics, and individual socioeconomic profiles. Selection and parameterization of variables in the decision model are informed by statistical analysis of data obtained from a discrete choice experiment.

3.2.1. Discrete choice model

This study assumes that consumers behave rationally and consider factors such as vehicle attributes, INE, and the accessibility of charging or gas stations when making purchase decisions. To assess the influence of these factors on purchase intentions, this paper employs a stated preference approach within a discrete choice experiment framework, which analyzes consumer preferences by observing choices across hypothetical purchase scenarios with varying attribute combinations (Higgins et al., 2017; Qian et al., 2019; Rudolph, 2016). Data was collected through a questionnaire comprising two main components: demographic information and a stated preferences survey. Following Patt et al. (2019), the demographic section includes questions on respondents' income, acceptable vehicle purchase price, place of residence, and availability of private charging infrastructure. The stated preferences section focuses on vehicle attributes, INE, and PrCP installation status. Specifically, the vehicle attributes considered are purchase price, driving range, refueling or recharging time, cost per 100 km of driving, and maintenance and insurance expenses (Rudolph, 2016). INE is measured by the number of charging or gas stations within a predefined radius of the respondent's residence (Sun et al., 2018). A discrete choice model is developed under the assumption that users choose between two vehicle types: ICEVs and EVs. Utility U_{ij} that user i derives from selecting vehicle type j consists of three components, as specified in Equation (1). X_j represents the explanatory variables, including vehicle attributes (purchase price, driving range, refueling/-recharging time, cost per 100 km of driving, and insurance and maintenance costs), INE (measured by the number of charging stations within a specified radius), and PrCP installation status (represented by a binary variable and equal to 1 if a PrCP is installed and 0 otherwise). Y_i denotes individual-level demographic characteristics, including gender, annual income, and age (Qian et al., 2019). ε_{ij} is the error term.

$$U_{ij} = \beta' X_j + \alpha' Y_i + \varepsilon_{ij} \tag{1}$$

To ensure the validity of the questionnaire design, we conducted a one-week pilot survey in December 2024, combining in-person visits to

Table 2
ABM-based studies on EV diffusion.

Reference	Consumer heterogeneity	PCP	PrCP	PCS subsidy	PCS subsidy phase-out	PCS spatial allocation
Zhang et al. (2011)	✓					
Eppstein et al. (2011)	✓					✓
Shafiei et al. (2012)	✓					
Xu and Bi (2024)	✓					✓
Sun et al. (2018)	✓	✓				✓
Y. Wang et al. (2023)	✓	✓	✓			✓
Luo et al. (2023)	✓	✓		✓		
Zhuge et al. (2021)	✓	✓	✓			✓
Zhuge et al. (2021)	✓	✓				✓
Wolbertus et al. (2021)	✓	✓				✓
Huang et al. (2021)	✓	✓		✓		
Pagani et al. (2019)	✓	✓	✓			✓
Silvia and Krause (2016)	✓	✓				✓
This study	✓	✓	✓	✓	✓	✓

Table 3
Maximum likelihood estimation results of the mixed logit regression.

Variables	Coeff.	Std. error	P-values
Vehicle price (10,000 RMB)	−0.060***	0.011	0.000
Driving range (100 km)	0.004***	0.0004	0.000
Refueling/Recharging time (minutes)	− 0.009***	0.001	0.000
Cost per 100 km (RMB)	−0.026***	0.005	0.000
Maintenance and insurance cost (10,000 RMB)	− 0.540***	0.063	0.000
Number of gas or charging stations (within 5 km)	0.018***	0.005	0.001
PrCP installation (=1 if PrCP installed)	0.504***	0.065	0.000
Income (100,000–150,000 RMB)	0.193	0.158	0.221
Income (150,000–200,000 RMB)	0.305*	0.167	0.066
Income (200,000–300,000 RMB)	0.182	0.170	0.285
Income (≥300,000 RMB)	0.489**	0.210	0.020
Gender (Male)	0.031	0.103	0.767
Age (25–34)	0.060	0.147	0.682
Age (35–44)	0.054	0.161	0.739
Age (45–54)	0.309	0.266	0.245
Age (≥55)	0.219	0.471	0.642
Constant	0.357	0.249	0.153
Log likelihood	− 2780.2399		

Notes: *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$. The number of observations is 533. The omitted reference categories are 'Income (50,000–100,000 RMB)' for income level, 'Female' for gender, and 'Age (18–24)' for age, due to multicollinearity.

4S stores across multiple districts of Beijing with online data collection. Feedback from respondents regarding the clarity and appropriateness of the questionnaire was collected during the survey and subsequently used to refine its content. During the formal survey, questionnaires were collected from April 2 through April 30, 2025. The regional distribution of the responses is reported in Appendix A, Table A3, while descriptive statistics of the survey data are presented in Tables A1 and A2. In total, 549 responses were collected through the Wenjuanxing platform,[7] of which 533 were deemed valid after data trimming. The cleaned data was analyzed using Stata 16.0, with a mixed logit model to estimate consumer preferences for the relevant factors. Estimated coefficients were obtained through the maximum likelihood method, and the results are summarized in Table 3.

As shown in Table 3, several vehicle attributes, including vehicle price, driving range, refueling/recharging time, cost per 100 km of driving, and maintenance and insurance cost, are found to be statistically significant. Particularly, the estimated coefficients for vehicle price, refueling/recharging time, cost per 100 km of driving, and maintenance & insurance cost are negative, suggesting that higher values of these attributes reduce consumer utility, which is consistent with theoretical expectations and aligns with prior research (Qian et al., 2019). With respect to the charging environment, both INE and PrCP

installation status exhibit statistically significant coefficients, each contributing positively to consumer utility. Notably, the impact of PrCP installation is much greater than that of having one PCS within a 5 km radius. This finding supports the conclusions of Qian et al. (2019) and Helveston et al. (2015), who argued that the availability of private charging infrastructure has a stronger influence on EV adoption compared to the convenience of public charging infrastructure. Regarding demographic characteristics, only the income categories of '150,000–200,000 RMB' and '≥ 300,000 RMB' exhibit statistically significant effects. The magnitude and direction of these estimated coefficients indicate that higher income levels are associated with a greater likelihood of EV purchase, which is consistent with the findings of Sun et al. (2018a,b). By contrast, the coefficients for gender and age turn out to be not statistically significant, indicating that these characteristics have little influence on EV purchase decisions.

3.2.2. Utility function

In the consumer sub-model, a mixed logit regression method based on survey data is used to construct a utility evaluation framework that incorporates vehicle attributes and environmental factors. As shown in Fig. 1, the framework consists of four components: (1) changes in vehicle lifespan over time (within the blue box), (2) comparison of vehicle attributes (within the red box), (3) evaluation of the EV charging environment (within the yellow box), and (4) calculation of EV purchase probability (within the green box). The blue box represents consumers who already own a vehicle (either EV or ICEV). For these consumers, vehicle lifespan decreases with each period, and once it reaches zero, they are reclassified as non-owners. The red box denotes vehicle attribute comparison, in which EV driving range and price are first evaluated. Consumers proceed to consider the charging environment only if both attributes meet expectations; if either falls short, they shift to purchasing an ICEV. Given that ICEVs are not subject to range anxiety, it is assumed that consumers will purchase an ICEV if its price falls below a

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[7] This platform specializes in professional questionnaire distribution and offers access to an extensive sample pool of approximately 6.2 million individuals, encompassing a wide spectrum of income levels, age groups, occupations, and other demographic characteristics.

preset acceptable threshold; otherwise, they exit the market without making a purchase. The yellow box corresponds to the assessment of the charging environment. When an EV's driving range and sale price meet expectations, consumers first check whether they already possess a PrCP or have permission to install one. If either condition is satisfied, the model calculates the probability of purchasing an EV with access to a PrCP.[8] If not, it is then assessed whether a PCS exists within 5 km[9]; if available, the probability of purchasing an EV without PrCP (but with access to PCS) is calculated. If no PCS is available, consumers instead consider an ICEV and evaluate its price. Finally, the green box refers to the calculation of EV purchase probability. After this probability is determined, a random number is drawn from a uniform distribution [0,1] to simulate the consumer's purchasing decision mechanism (Zhu and Ma, 2025): If the calculated probability is greater than or equal to the random number, the consumer purchases an EV; otherwise, they consider an ICEV and evaluate whether its price meets expectations.

To account for EV consumer heterogeneity, we build on Wang et al. (2023) by analyzing the correlations between annual income and key parameters such as annual driving mileage and the proportion of time spent charging at PCSs. Based on the direction and strength of these correlations, we differentiate parameter values across income groups. Furthermore, drawing on the survey data, we establish income distribution profiles for urban and suburban populations. Details of the income distribution and correlation analysis are provided in Appendix A (Table A2 and Table A4, respectively). Based on the previously introduced discrete choice model, the utility consumer i derives from choosing vehicle type j at time t, which is $U_{i,j,t}$, can be specified in Equation (2):

$$U_{i,j,t} = \beta_1 * (P_{j,t} - S_{pur,t}) + \beta_2 * C_{dri,i,j} + \beta_3 * C_{other,j} + \beta_4 * R_{j,t} + \beta_5 * T_j + \beta_6 * N_{i,j,t} + \beta_7 * B_i + \varepsilon_{i,j,t} \quad (2)$$

Where $P_{j,t}$ is the price of vehicle type j at period t, and $S_{pur,t}$ denotes the EV purchase subsidy at period t. $C_{dri,i,j}$ represents the cost per 100 km of driving for consumer i using vehicle type j, while $C_{other,j}$ is the maintenance and insurance cost of vehicle type j. $R_{j,t}$ denotes the driving range of vehicle type j at period t, and T_j is the time required to fully refuel or recharge vehicle type j. $N_{i,j,t}$ refers to the number of charging or gas stations within a 5-km radius of consumer i with vehicle type j during period t. B_i is a binary indicator equal to 1 if consumer i has access to a PrCP, and 0 otherwise. β is a vector of estimated coefficients, and $\varepsilon_{i,j,t}$ is the error term. It is worth noting that the influence of demographic attributes on consumer purchase decisions is omitted from the model specification in this paper. While this simplification could be seen as problematic, as a p-value above 0.1 does not necessarily imply a lack of effect (Scorrano and Danielis, 2025). We proceed with this assumption for the sake of model parsimony. Accordingly, the probability user i

chooses an EV during period t, denoted as $Pr_{i,e,t}$, is formulated as shown in Equation (3):

$$Pr_{i,e,t} = \frac{e^{(U_{i,e,t} - \varepsilon_{i,e,t})}}{e^{(U_{i,e,t} - \varepsilon_{i,e,t})} + e^{(U_{i,f,t} - \varepsilon_{i,f,t})}} \quad (3)$$

3.2.2.1. Cost of 100-km driving. This paper assumes that EV users fall into two categories: those who rely exclusively on PCS and those who have access to PrCPs (although the latter may also use public charging facilities). The charging capacities of public and private stations are denoted as K_{pub} and K_{pri}, respectively. For users who rely solely on PCSs, the per-100-km driving cost, $C_{dri,i,e,pub}$, is determined by three factors: the composite electricity price at PCS P_{elc}, the service fee per unit (kWh) of electricity P_{ser}, and the parking fee incurred per unit (kWh) of electricity charged while charging P_{park}.[10] For consumers with PrCPs, the overall charging cost, $C_{dri,i,e,pri}$, is calculated by combining the costs of PCS and PrCP usage. This total cost depends on the share of charging time that individual i spends using PCP, represented by y_i. The specific cost is calculated using Equation (4) for users who rely only on PCSs, and Equation (5) for those with access to PrCPs.

$$C_{dri,i,e,pub} = h_e * (P_{elc} + P_{ser} + P_{park}) \quad (4)$$

$$C_{dri,i,e,pri} = h_e * \frac{K_{pub} * (P_{elc} + P_{ser} + P_{park}) * y_i + K_{pri} * P_{pri} * (1 - y_i)}{K_{pub} * y_i + K_{pri} * (1 - y_i)} \quad (5)$$

Where y_i denotes the percentage of total charging time that consumers with PrCPs spend using PCSs,[11] and h_e represents the electricity consumption per 100 km of driving for an EV. P_{pri} is the charging price of PrCPs and is assumed to be time-invariant.[12] The composite electricity price at PCS, P_{elc}, is calculated by multiplying the share of charging volume in each time-of-use period by the corresponding hourly electricity rate[13] and then summing across all time periods, as shown in Equation (6).

$$P_{elc} = \sum_{s=0}^{23} \sigma_s * P_{elc,s} \quad (6)$$

Where σ_s represents the share of charging volume in hour s, and $P_{elc,s}$ is the corresponding electricity pricing rate. For ICEV consumers, the cost per 100 km of driving, $C_{dri,i,f}$, is calculated as the product of the fuel price P_g and the fuel consumption per 100 km of driving h_f, as shown in Equation (7). In this case, B_i is set to 0, indicating that access to PrCPs will not affect the utility from using ICEVs.

$$C_{dri,i,f} = h_f * P_g \quad (7)$$

3.2.2.2. Maintenance and insurance costs. The total maintenance and

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[8] In the Chinese market, most automobile manufacturers provide EV consumers free PrCPs and installation services, making it relatively easy for the consumers to access PrCPs. But in fact, the installation of a PrCP requires both a dedicated parking space and approval from the property management company. But according to a report by the China Consumer Association, the main reasons EV users do not install PrCP are the absence of a dedicated parking space or property management company's refusal, which is consistent with the findings of EVCIPA (2020). Also, although some consumers do not install PrCPs even the conditions above are met, such case are not the main reason. Therefore, this paper makes an assumption and simplification: once installation conditions are satisfied, consumers are assumed to install PrCPs. Source: https://www.cca.org.cn/Detail?catalogId=475800366178373&contentType=article&contentId=521575306829893.

[9] According to the investigation by the China Consumers Association, 96 % of EV users live within 5 km of PCSs. Based on this, this study assumes that EV consumers would consider the presence of a PCS within 5 km when making purchase decisions. Source: https://www.cca.org.cn/Detail?catalogId=475800366178373&contentType=article&contentId=521575306829893.

[10] For computationally simplicity, we assume a constant parking fee of approximately 4 RMB per hour. Given that the capacity of a public charging pile is set at 30 kW, the corresponding parking fee incurred per unit (kWh) of electricity charged is calculated as 4/30 = 0.13 RMB per kWh.

[11] In the main text, y_i refers to the proportion of total charging time consumer i spent using PCS (i.e., Time of charging at PCS/(Time of charging at PCS + Time of charging at PrCP)). However, in the questionnaire, y_i was defined in opposite way for ease of respondent understanding, namely, as the share of charging time spent using PrCP (i.e., Time of charging at PrCP/(time of charging at PCS + Time of charging at PrCP)). Accordingly, the 'share of charging time at PrCP' reported in Table A1 does not appear in the main text.

[12] The government has mandated regulations on electricity pricing for PrCPs (NDRC, 2014). Under this policy, a unified residential electricity rate is applied, which means that P_{pri} remains constant over time. Source: https://zfxxgk.ndrc.gov.cn/web/iteminfo.jsp?id=19564.

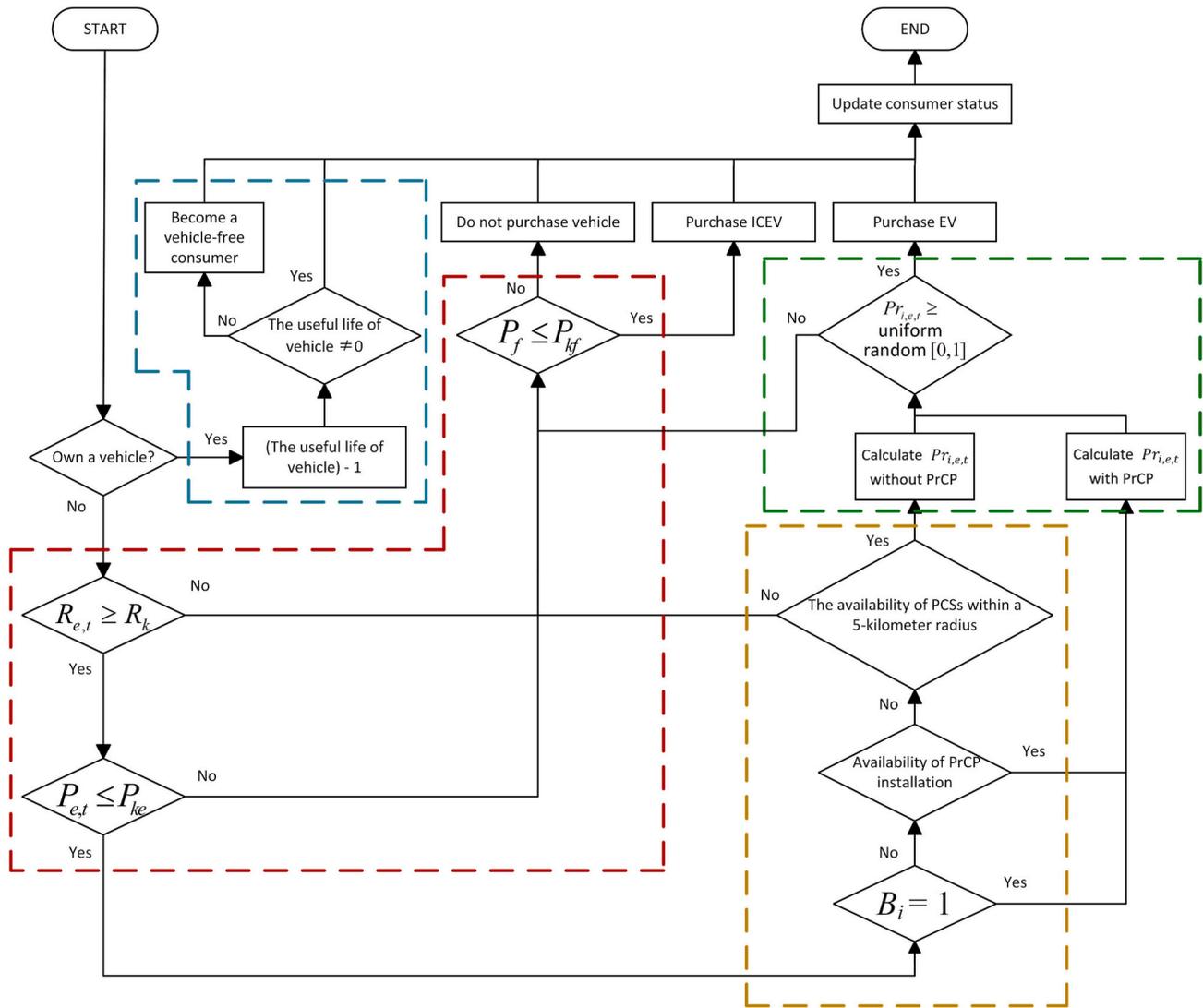[13] The time-of-use charging volume shares are from: https://www.evcipa.org.cn/newsinfo/8137317.html.

Fig. 1. The decision-making process of consumers.

insurance cost for vehicle type j is calculated by multiplying the estimated maintenance and insurance costs per period by the expected number of periods that the vehicle will be in use, as shown in Equation (8). Specifically, $C_{ins,j}$ denotes the insurance cost, $C_{mai,j}$ represents the maintenance cost, and η_j refers to the estimated service life (in periods) of vehicle type j.

$$C_{other,j} = (C_{ins,j} + C_{mai,j}) * n_j \tag{8}$$

3.2.2.3. EV pricing. With respect to EV pricing, this paper follows the approach of Huétink et al. (2010) for hydrogen vehicle pricing, assuming that EV prices gradually decrease as market stock increases, as shown in Equation (9).

$$P_{e,t} = P_{e,0} * \left(\frac{Q_{e,0}}{Q_{e,t-1}} \right)^{\omega} \tag{9}$$

Where $P_{e,0}$ is the initial price of EVs, and $Q_{e,0}$ is the initial stock of EVs. $Q_{e,t-1}$ represents the stock of EVs in period *t-1*, and ω denotes the learning rate, with higher values of ω indicating a faster decline in EV prices.

3.2.2.4. EV driving range. To model the evolution of EV driving range over time, this paper adopts an S-shaped technology lifecycle curve to

represent technological maturity, which in turn affects driving range. Since EV driving range is closely tied to advances in battery and related technologies (Z. Liu et al., 2023), and given that the number of patents can serve as a proxy for technological progress, we follow the approach of Shen et al. (2021) by linking technological maturity to driving range. In their work, technology diffusion theory is applied to fit an S-curve to the growth of EV-related patents, with the maximum number of patents estimated. Technological maturity in each period is then calculated as the ratio of the cumulative number of patents to this estimated maximum. While the same method is adopted in this study, adjustments are made to account for differences in the simulation period: in Shen et al. (2021), each simulation step represents one month, whereas in this study, each step corresponds to three months. EV driving range and technological maturity are calculated using Equations (10) and (11), respectively.

$$R_{e,t} = \frac{R_{e,0}}{(1 - Tech_t + Tech_0)^2} \tag{10}$$

$$Tech_t = \frac{1}{1 + e^{-\tau*[(3*t-2)+667-\theta]}} \tag{11}$$

Where $Tech_t$ denotes the technological maturity of EVs at time *t*, and $Tech_0$ is the initial level of technological maturity. τ represents the growth rate of the S-curve, while θ indicates its inflection point—the

time at which the growth rate begins to slow. To avoid unrealistic or uncontrolled growth in EV driving range over time, an upper bound is also set for the maximum driving range.

3.2.2.5. Driver population. China's automotive market has experienced steady growth in both vehicle ownership and the number of licensed drivers(Kong, 2025). Although the annual growth rate of new drivers has gradually declined, the market is expected to remain in an expansion phase until approximately 2028. From a long-term perspective, the Chinese automotive market is projected to sustain growth through 2050 (Hao et al., 2011). In this study, the simulation period covers the real-world timeframe from 2019 to 2031. To simplify the model, and based on the observed annual trend, we assume that the growth rate of licensed driver quantity each period is time-invariant and represented by γ_d. The population size of the simulated space in period t, denoted as M_t, is calculated using Equation (12), while the number of newly added potential consumers in each period, ΔM_t, is determined using Equation (13).

$$M_t = M_{t-1} * (1 + \gamma_d) \tag{12}$$

$$\Delta M_t = M_t - M_{t-1} \tag{13}$$

3.2.2.6. PrCP installation eligibility. The installation of PrCP requires several conditions, most notably sufficient load capacity and access to dedicated parking spaces. To promote EV adoption, the Chinese government issued a policy in 2015 mandating that newly built neighborhoods include provisions for charging infrastructure (General Office of the State Council of the P.R.C, 2015).[14] However, many communities built before 2015 were not equipped with sufficient electrical infrastructure to support PrCPs, and the majority of parking spaces in these neighborhoods do not meet the technical requirements for PrCP installation, particularly in older communities built before 2000. These aging communities account for nearly 40 % of residential areas in 20 major cities across China.[15] Based on the ongoing renovations of older communities, this study assumes that the proportion of the population meeting PrCP installation conditions will gradually increase, reflecting continuous improvements in residential infrastructure. Nevertheless, due to the persistent shortage of dedicated parking spaces in China,[16] our model constrains this proportion from even reach 100 %. To simplify the modeling process, it is further assumed that, in each period, a portion of the population without PrCP installation conditions, denoted as $M_{t,np}$, acquires the necessary conditions at a fixed rate, γ_n. This specification is formulated in Equation (14):

$$M_{t+1,np} = M_{t,np} * (1 - \gamma_n) \tag{14}$$

Where γ_n represents the conversion rate of PrCP installation eligibility in each period.

3.3. EVCI operator sub-model

In this study, the EVCI operator evaluates both operational performance and market charging demand to determine whether to deploy new PCSs. The operator's revenue primarily comes from charging fees and government subsidies, while costs consist of construction, land rent, maintenance, and electricity procurement (Q. Zhang et al., 2018). ROI serves as a comprehensive metric for evaluating the balance between operating profits and costs (Schroeder and Traber, 2012). Although

charging demand is directly linked to the number of EV users, it is also shaped by a complex interplay of charging prices, electricity procurement costs, operating expenses, and construction costs (Q. Zhang et al., 2018). Therefore, analyzing charging demand requires a dual focus on both the scale of EV users and the characteristics of the existing public charging infrastructure. The utilization rate serves as an effective indicator for the relationship between the number of consumers and the number of PCSs across different regions. By analyzing utilization rates, the operator can better identify regional charging demand patterns and adjust charging station deployment strategies accordingly. As the primary objective of this paper is not to examine competitive dynamics among operators, the model is simplified by assuming a single operator in the market. The decision-making process of this operator is illustrated in Fig. 2. If the operating profit in a given period is positive, the operator undertakes cost improvement measures for PCSs. Based on the updated costs and current profit, ROI is recalculated. When ROI exceeds a predefined threshold ROI^{min}, the operator deploys additional stations. Deployment decisions are guided by a comparison of regional utilization rates with the overall average, with new PCSs allocated in areas showing above-average demand.

3.3.1. Operating profit

The operating profit of PCSs mainly depends on service fees, parking fees, operating costs, OSs, and advertising revenue. Revenue from parking and service is directly tied to consumer charging demand—higher demand leads to higher operating profit. At the same time, as the number of PCSs increases, operating costs rise correspondingly, while advertising revenue also grows due to the expansion of infrastructure.[17] The operator's operating profit in period t, π_t, is given by Equation (15).

$$\pi_t = \sum_{i=1}^{n} E_i^c * (P_{ser} + P_{park}) - \sum_{g=1}^{n} C_{op}^g + S_{op,t} + A_{ads} * \sum_{h=1}^{m} N_{h,e,t} \tag{15}$$

Where E_i^c represents the electricity demand of user i during each period and is calculated in Equation (16). A_{ads} denotes the advertising revenue generated by each PCS per period, and C_{op}^g is the operating cost of PCS g per period. $N_{h,e,t}$ indicates the number of the stations in region h during period t, while $S_{op,t}$ represents the government OSs provided in period t.

$$E_i^c = \frac{D_i}{100} * h_e \tag{16}$$

$$C_{op}^g = \gamma_c * C_{con}^g \tag{17}$$

As shown in Equation (16), the electricity demand of user i per period, denoted as E_i^c, is determined by the user's driving distance in that period D_i and the EV's energy consumption per 100 km h_e. The operating cost of PCS g in each period, C_{op}^g, is calculated based on its construction cost C_{con}^g and the ratio of operating to construction costs γ_c, as expressed in Equation (17). Especially, E_i^c is time-invariant, and the construction cost of PCS g, C_{con}^g, equals the unit construction cost in period t, $C_{con,t}$, when the station was built.

3.3.2. Research and development cost

The growth in the number of EVs increases charging demand, which requires the operator to expand the number of PCSs to accommodate more users. However, the construction of new stations directly affects the operator's ROI. To address this, the operator allocates a portion of its funds to research and development (R&D), with a particular focus on reducing construction costs of PCSs. Following the description of operator R&D investment in Sun et al. (2016), this study constructs a

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[14] This report is accessed at: https://www.gov.cn/zhengce/content/2015-10/09/content_10214.htm.

[15] The information is from the Beike Research Institute report: https://research.ke.com/121/ArticleDetail?id=274.

[16] Relevant information is accessed from: https://capital.people.com.cn/n1/2020/0708/c405954-31775313.html.

[17] The installation of PCSs does not directly affect the operator's profit. This is because, based on our field investigation, most PCSs are provided by automobile manufacturers at the time of vehicle purchase, with both equipment and installation services offered to users free of charge.
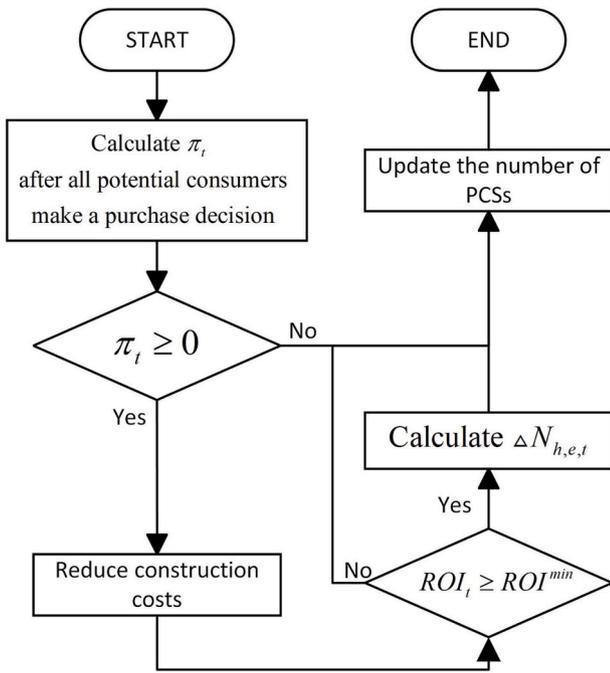
Fig. 2. The decision-making process of the EVCI operator.

simplified cost-improvement R&D model. In this model, the operator allocates a portion of its operating profit in period t to R&D investment, denoted as RD_t, as defined in Equation (18).

$$RD_t = \lambda_t * \pi_t \tag{18}$$

Where λ_t represent the proportion of profit allocated to R&D investment in period t. The R&D investment in period t, denoted as RD_t, determines the construction cost $C_{con,t}$ for that period. However, construction costs cannot decrease indefinitely and are subject to a lower bound, denoted as C_{con}^{min}. The reduction in construction cost for each period, $\Delta C_{con,t}$, is calculated using Equation (19).

$$\Delta C_{con,t} = \mu * RD_t * v * \left(C_{con,t-1} - C_{con}^{min} \right) \tag{19}$$

Where μ represents the proportion of R&D investment allocated specifically to cost reduction, and v reflects the effectiveness of R&D in lowering construction costs. After calculating the cost reduction with Equation (19), the operator updates the construction cost according to Equation (20).

$$C_{con,t} = C_{con,t-1} - \Delta C_{con,t} \tag{20}$$

3.3.3. Public charging stations deployment

The deployment of PCSs by EVCI operators is primarily driven by two factors: RIO and charging demand. The former is evaluated against a minimum acceptable threshold, ROI^{min}, which must be exceeded for new investments to proceed. The latter is assessed through regional utilization rates.[18] Following Luo et al. (2023), ROI per period, ROI_t, is calculated as the ratio of operating profit to initial construction cost, as expressed in Equation (21).

$$ROI_t = \frac{\overline{\pi_t}}{C_{con,t} - (z * K_1 * s_{con})} \tag{21}$$

Where z denotes the number of PCPs, K_1 is the charging capacity of a single station, s_{con} represents the CS for each station, and $\overline{\pi_t}$ is the

average operating profit per station, which is calculated based on Equation (22). For computational simplicity, it is assumed that all charging stations have identical charging capacity and an equal number of charging piles, with variations across stations limited to construction and operation costs.

$$\overline{\pi_t} = \frac{\pi_t}{\sum_{h=1}^{m} N_{h,e,t}} \tag{22}$$

When the ROI exceeds the threshold ROI^{min}, the operator proceeds with the construction of a new PCS. The overall average utilization rate of all PCSs in the simulated space, denoted as $\overline{r_t}$, is calculated using Equation (23).

$$\overline{r_t} = \frac{\sum_{h=1}^{m} \sum_{i=1}^{n} E_{i,h}^c}{\sum_{h=1}^{m} \left(N_{h,e,t} * E_{max} \right)} \tag{23}$$

Where E_{max} denotes the maximum charging volume that a single station can offer per period. Once the overall average utilization rate is obtained, the regional utilization rate for region h in period t, $\overline{r_{ht}}$, is determined through Equation (24).

$$\overline{r_{h,t}} = \frac{\sum_{i=1}^{n} E_{i,h}^c}{N_{h,e,t} * E_{max}} \tag{24}$$

The average utilization rate of PCSs effectively reflects EV charging demand within a region. A higher utilization rate indicates stronger demand and signals an undersupply of charging infrastructure, thereby indicating the need for additional PCS deployment. The operator identifies regions with utilization rates higher than the average by comparing the regional average utilization rate $\overline{r_{h,t}}$ with the overall average $\overline{r_t}$, and deploys new PCSs in these regions.[19] However, the expansion of PCSs is inherently constrained, as additional construction and operation lead to higher costs. Given this fact, it is assumed that the operator deploys additional PCSs only in regions with above-average demand, with the number of newly deployed stations calibrated to ensure that regional utilization does not exceed the overall average rate, while no new PCSs are deployed in regions without excess demand. To ensure that regional utilization rates do not surpass the overall average, operators apply Equation (25) to calculate the number of additional stations, $\Delta N_{h,e,t}$, needed in each region. The results are rounded up to the nearest integer to avoid fractional values in $\Delta N_{h,e,t}$. Since the primary objective of this study is to examine the impact of public policies on EV diffusion rather than the market effects of specific PCS locations, the model assumes that newly added PCSs are randomly distributed within targeted regions. Furthermore, charging demand is assumed to be evenly distributed across all PCSs in each region.

$$\Delta N_{h,e,t} = \left\lceil \frac{\sum_{i=1}^{n} E_{i,h}^c}{\overline{r_t} * E_{max}} - N_{h,e,t} \right\rceil \tag{25}$$

3.4. Government sub-model

The government provides subsidies to both EV consumers and EVCI operator, which aligns with real-world policy practices. Consumers receive EV purchase subsidies, while operator obtains two forms of financial support: OSs and CSs for charging infrastructure.

3.4.1. EV purchase subsidy

The simulation begins in 2019, coinciding with the period when EV purchase subsidies significantly boosted EV adoption before being

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completely phased out by the end of 2022 (T. Zhang et al., 2024). The specific subsidy levels during this period are summarized in Table 4.

3.4.2. Operational subsidy

The amount of OSs is determined by the total volume of electricity charged. To prevent excessive subsidy expenditures arising from abnormally high charging volumes, this study imposes a cap on the maximum subsidized charging volume per charging pile within each period, which is linked to the pile's power capacity. Referring to subsidy policies implemented by various provincial governments in China, this paper defines a cap, $S_{op,max}$, representing the maximum subsidized charging volume per unit of a charging pile capacity (kW) in each period. The formula is given in Equation (26).

$$s_{op,h,t} = \begin{cases} S_{op,max}*z*K_1*s_{op}*N_{h,e,t}, & \dfrac{\sum_{i=1}^{n} E_{i,h}^c}{z*K_1*N_{h,e,t}} > S_{op,max} \\[4mm] \sum_{i=1}^{n} E_{i,h}^c*s_{op}, & \dfrac{\sum_{i=1}^{n} E_{i,h}^c}{z*K_1*N_{h,e,t}} \le S_{op,max} \end{cases} \tag{26}$$

Where s_{op} represents the operational subsidy rate per unit of electricity charged. After calculating the subsidy amount for each region $s_{op,h,t}$, the total OSs for period t, denoted as $s_{op,t}$, are obtained by aggregating regional amounts using Equation (27) and subsequently distributed to the operator.

$$s_{op,t} = \sum_{h=1}^{m} s_{op,h,t} \tag{27}$$

3.4.3. Construction subsidy

The amount of CSs is determined by the capacity of newly installed PCPs. The total CSs offered by the government in period t, $s_{con,t}$, are calculated using Equation (28). Detailed descriptions of the variables are provided in Appendix B.

$$s_{con,t} = z*K_1*s_{con}*\sum_{h=1}^{m} \Delta N_{h,e,t} \tag{28}$$

4. Model initialization

4.1. Parameter settings

Since this study focuses on the diffusion of EVs in China from 2019 to 2031, the initial parameter settings are based on the characteristics of the Chinese EV market in 2019. Data sources include official EV statistics, government and industry reports, survey findings, and other relevant real-world data. According to the China Urban Construction Statistical Yearbook 2019,[20] the proportions of urban and suburban areas are set at 9 % and 91 %, respectively. In the simulation, a spatial area of 10,000 square kilometers was established and scaled down by a factor of 1:100. Drawing on 2019 Geode Map Point of Interest data for China's first batch of EV pilot cities and the National Bureau of Statistics of China (NBSC, 2020), we assume that 50 % of ICEVs, 80 % of EV consumers, and 80 % of PCSs are located within urban areas. The share of gas stations in urban areas is set at 24.5 %.[21] Attributes of ICEVs and EVs, including purchase price and the construction cost of gas or charging stations, are determined based on 2019 market data. The total number of vehicles is estimated using the ratio between the aggregate

area of China's first batch of EV pilot cities in 2019 and the corresponding number of private vehicles in those cities, yielding a ratio of 1:273.84. According to this ratio, an area of 10,000 km² corresponds to approximately 2.7384 million vehicles. For simulation purposes, this figure is scaled down to 27,384, and the number of EVs is set to 504, reflecting the proportion of EV ownership relative to private vehicles in 2019 (Jiang, 2020). The numbers of PCSs and PrCPs are determined according to the 2019 vehicle-to-charging pile ratio of 3.13:1 and the fact that PrCPs account for 57.77 % of total charging piles (China Electric Vehicle Charging Infrastructure Promotion Alliance, 2020), resulting in 7 PCSs and 93 PrCPs. Furthermore, the number of gas stations is set to 20, in accordance with the ratio of gas stations to private vehicles observed in the first batch of EV pilot cities. Detailed parameter sources are provided in Appendix C. To account for heterogeneous consumer attributes, demographic characteristics data such as annual income was collected through a questionnaire survey. Targeted questions captured income distributions for both urban and suburban consumers. Analysis of the survey responses revealed that several parameters, including driving mileage, PCPs usage behavior, minimum acceptable EV driving range, and maximum acceptable vehicle purchase price, are correlated with income. Accordingly, following Wang et al. (2023), parameter values are assigned to specific income groups.

The limited consideration of PrCPs in the existing literature makes their parameterization a key challenge in this study. In China, PrCP installation requires both a dedicated parking space and adequate electrical infrastructure. These constraints exclude most neighborhoods built prior to 2010. Using the national neighborhood dataset provided by the Anhjuke[22] platform and selecting Shenzhen as a case study, we conduct a statistical analysis of neighborhoods built after 2010 in urban and suburban areas. The results show that 21.93 % are located within urban areas, while 53.02 % are in suburban areas. Since only a portion of vehicle owners have access to dedicated parking spaces,[23] the proportions of individuals meeting PrCP installation requirement are adjusted from the original 21.93 % (urban) and 53.02 % (suburban) to 15 % and 45 %, respectively. China is implementing a nationwide renovation program targeting aging neighborhoods, with many local governments including neighborhoods built before 2010 in their renovation plans.[24] As of 2024, 280,000 neighborhoods have been renovated.[25] According to Equation (14), the per-period conversion rate for meeting PrCP installation conditions is approximately 0.24. However, renovation data up to 2023[26] show that only 8.55 % of users gained access to new parking spaces through neighborhood upgrades and, not all of these spaces are technically suitable for PrCP installation. Field investigations indicate that approximately 76 % of renovated parking spaces meet the necessary technical requirements. Taking the factors above into account, the actual per-period conversion rate, γ_n, is calculated as: $\gamma_n = 0.24*8.55\%*76\% = 0.0157$.

The relevant parameter settings for the EVCI operator are provided in Appendix C. Based on the 2019 market shares of direct current (DC) and alternating current (AC) charging piles, as well as their respective capacities, the capacity of each PCS is set at 30 kW.[27] The cost of a single

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[20] The China Urban Construction Statistical yearbook 2019 is accessed through: https://www.mohurd.gov.cn/gongkai/fdzdgknr/sjfb/tjxx/jstjnj/index.html.

[21] The proportion of gas stations is determined from: https://zhuanlan.zhihu.com/p/479161778.

[22] Anjuke is a well-known real estate information service platform in China, with a vast property listings database covering cities nationwide.

[23] We arrive at this conclusion with reference to: https://fgw.sz.gov.cn/zwgk/qt/tzgg/content/post_4589542.html.

[24] Examples can be found through the following links: https://zjw.wuhu.gov.cn/openness/public/6596411/39951772.html,https://jnszjj.jining.gov.cn/art/2025/3/17/art_9687_2706558.html,https://www.fujian.gov.cn/zwgk/zxwj/szfbgtwj/202009/t20200915_5386105.htm.

[25] More details on this can be found at: https://www.gov.cn/zhengce/202505/content_7024516.htm.

[26] Details on the renovation data is assessed at: https://www.gov.cn/lianbo/bumen/202401/content_6929176.htm.

[27] The market shares and costs of charging piles is at: https://mp.weixin.qq.com/s/cOHUkUWx865Y3qM5qaK_eA.

Table 4
The amount of EV purchase subsidies (2019–2022).

Year	2019		2020		2021		2022	
Driving Range (km)	[250,400)	[400,∞)	[300,400)	[400,∞)	[300,400)	[400,∞)	[300,400)	[400,∞)
Subsidy amount (100,000 RMB)	1.8	2.5	1.62	2.25	1.3	1.8	0.91	1.26

Source: https://www.gov.cn/zhengce/zhengcewenjianku/

30 kW DC PCP is approximately 40,000 RMB.[28] In addition to equipment costs, the construction of PCS also includes civil engineering and material expenses, estimated at around 170,000 RMB.[29] Accordingly, the total cost of building a PCS equipped with ten 30 kW PCPs is estimated at 570,000 RMB. The annual operating cost, which consists of maintenance and rental expenses, is assumed to be 7.2 % of the initial construction investment (Hu et al., 2020). Given that the model adopts a quarterly time step (four periods per year), the operating cost per period is therefore set at 1.8 % of the construction cost. Both CSs and OSs are parameterized based on official policy documents issued by provincial governments.

The simulation is conducted in NetLogo 6.4, with a random seed applied to ensure reproducibility of results. Each scenario is executed 50 times, and the average values across these runs are used for analysis. The initial spatial configuration of the simulation environment is presented in Fig. 3.

4.2. Verification

This paper uses the EV penetration rate as a key metric to validate the robustness and accuracy of the model. The EV penetration rate, a widely used indicator of EV adoption, is defined as the proportion of EV sales relative to total vehicle sales within a given period. As shown in Fig. 4, the simulated EV penetration rates generated by our model are compared with actual market data from 2019 to 2024, sourced from the China Association of Automobile Manufacturers. The simulated penetration trend closely follows the observed market trajectory. Model accuracy is further evaluated using the Mean Absolute Percentage Error (MAPE) and the coefficient of determination R^2, which are 11.88 % and 0.968, respectively. According to Zeng et al. (2017), an MAPE below 20 % indicates good predictive performance. Moreover, the R^2 value, being close to 1, indicates that the model effectively captures the variability in EV market penetration.

In the simulation, several parameter settings are derived from field investigations or assumptions, such as the proportion of the population in urban and suburban areas that meet the conditions for PrCP installation, the conversion rate of installation eligibility, and the minimum acceptable ROI for EVCI operator, proportion of R&D investment, effectiveness of R&D in construction cost reduction, and the maximum distance within which consumer is able to recognize the presence of a PCS. As the values of these parameters are influenced by the scope and representativeness of the field survey, a sensitivity analysis is conducted on these seven variables to evaluate their impact on model outcomes. The impact is measured in terms of the EV penetration rate.

As shown in Fig. 5, the initial proportion of the population in urban and suburban areas with PrCP installation eligibility has only a limited impact on EV penetration. This is because, in the early stages of EV market development, the overall EV market size remains small, so increases in the share of people with installation eligibility exert only a marginal effect on penetration. By contrast, variations in the conversion rate of installation eligibility and the minimum acceptable ROI for EVCI operators have a more pronounced influence. The conversion rate

directly affects the number of consumers with access to PcCPs in the middle and late stages of EV diffusion. As the market matures, EVs begin to outperform ICEVs, and accelerated residential infrastructure upgrades enable some consumers who initially lacked installation conditions and lived far from PCS to become more inclined to purchase EVs. Meanwhile, ROI^{min}, which represents the minimum acceptable ROI for operator, influences the pace of PCS deployment and thereby affects EV penetration trajectories. The differences in results regarding the proportion and effectiveness of R&D investment in construction cost reduction are not substantial. This may be because these parameters do not directly affect consumer utility. Instead, their influence is transmitted through an extended causal chain: faster cost reductions improve ROI, which in turn facilitates the deployment of additional PCSs, and only then increases consumer utility. Along this chain, the effect of these parameters becomes progressively attenuated. By contrast, improvements in consumers' recognition of PCS have a marked effect on EV penetration. Enhancing this penetration enables more consumers to recognize the existence of nearby PCSs, thereby increasing their willingness to purchase EVs and ultimately boosting EV adoption. Overall, the sensitivity analysis results confirm that the model responds realistically to parameter changes and captures real-world market dynamics, suggesting that it effectively simulates the actual process of EV diffusion.

5. Results and discussion

5.1. Baseline simulation results

5.1.1. Spatial distribution of EVs and EVCI

Fig. 6 illustrates the spatial distribution of EVs and EVCI across different time periods under the baseline scenario. This visualization enables an analysis of urban-suburban differences in spatial diffusion patterns. During the first 10 periods, constrained by the relatively limited attributes of EVs, there is no significant difference in the number of EV users between urban and suburban areas. However, the number and density of PCSs in urban areas begin to exceed those in suburban areas during these periods. By period 30, both EVs and PCSs exhibit a distinct diffusion pattern: urban areas continue to experience rising densities of EV and PCSs, while suburban areas begin to form small clusters of EV users, accompanied by corresponding PCS installations. By this stage, PrCPs have already been widely distributed across suburban areas. By period 52, the stocks of EVs and PCSs continue to grow in both urban and suburban areas. In suburban areas, however, the expansion of PCSs is constrained by residents' strong preference for PrCPs. The widespread availability of PrCPs not only enhances local EV adoption but also fosters more concentrated clusters of EV users. In areas where PCS coverage remains limited, PrCPs are instead distributed more sporadically across the landscape.

5.1.2. EV diffusion

5.1.2.1. EV penetration rate.
Fig. 7 presents the EV penetration rates in urban areas, suburban areas, and the overall region. Under the baseline scenario, the EV penetration rate increases rapidly during the early and middle stages, before gradually leveling off in the later stages and ultimately stabilizing at about 79.78 %. This plateau occurs because large-scale EV adoption has already taken place, while the main drivers of further penetration, price and driving range, improve at a slower pace in the later periods. Fig. 8 illustrates the temporal evolution of EV purchase

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[28] The price of a single 30 kW DC PCP is at: https://www.iimedia.cn/c400/66231.html.

[29] The civil engineering and material expenses is at: https://zfxxgk.nea.gov.cn/2023-03/02/c_1310702541.htm.
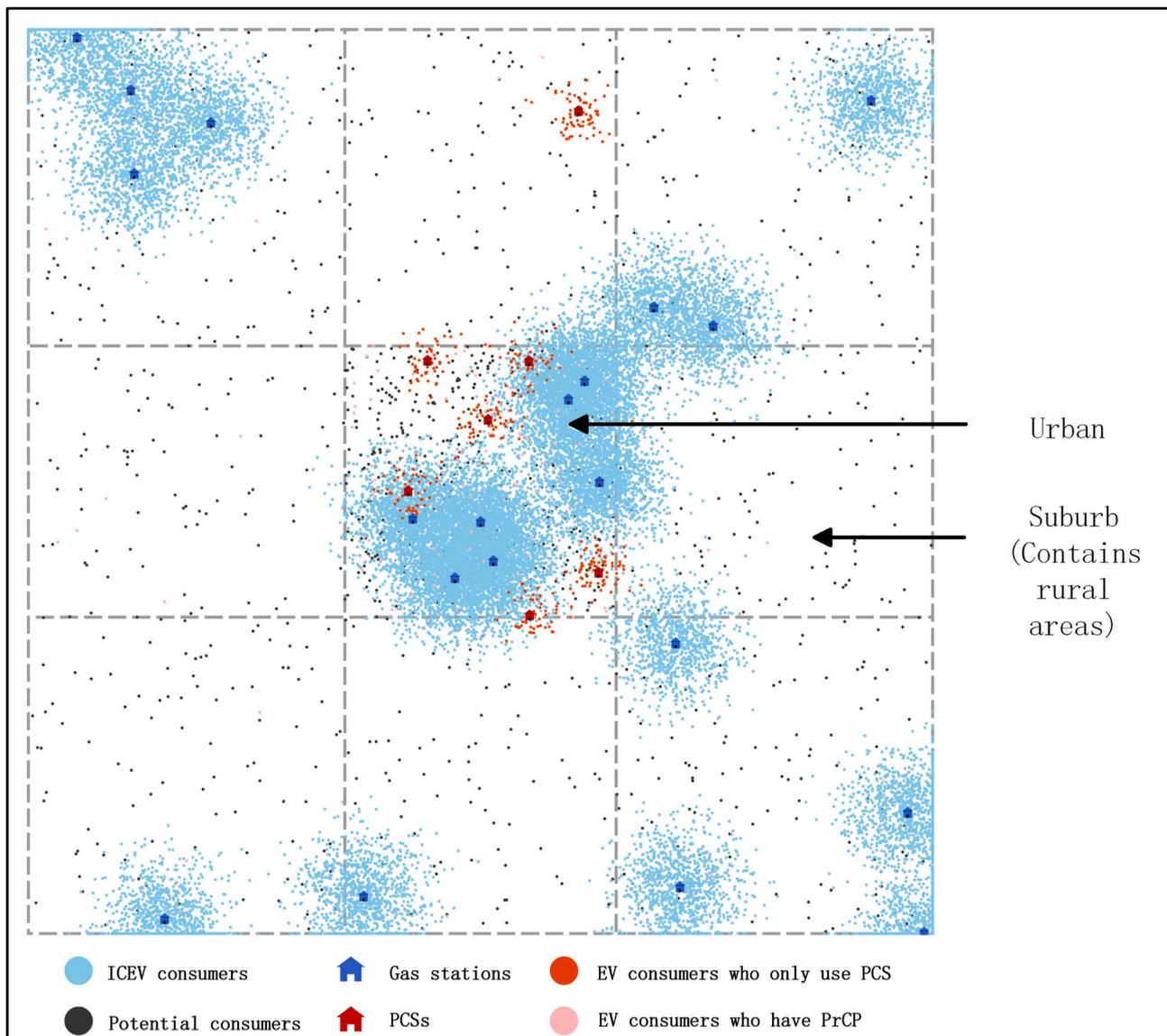
Fig. 3. Initial spatial configuration of the simulation environment.

price and driving range. It can be observed that the rate of price decline slows in the later stages, while driving range gradually stabilizes as technology matures. It is worth noting that there is a significant difference in EV penetration between urban and suburban areas, and this relationship reverses over time as charging infrastructure evolves. In the early stages, when the densities of PCSs in urban and suburban areas are relatively similar, the EV penetration rate in urban areas is lower than that in suburban areas. This finding aligns with Yang et al. (2024) and Chandra (2022), who suggest that when the densities of EVCI are comparable across regions, suburban consumers are more likely to purchase EVs compared to their urban counterparts. This is because detached housing in non-urban areas facilitates the installation of PrCPs. However, as the density of PCSs in urban areas increases during the mid-to-late stages, EV adoption in urban areas rapidly surpasses that in suburban areas, driven by the INE mechanism. At its peak, the gap in penetration rates reaches 16 %.

5.1.2.2. Vehicle market stock. As shown in Fig. 9, the stock of ICEVs exhibits an upward trend in the early stages and peaks in the middle stage (around 2024), generally consistent with projections by Sinopec.[30] By contrast, after a period of slow initial growth, the stock of EVs increases rapidly during the mid-to-late stages, driven by the gradual phase-out of ICEVs and growing consumer preference for EVs. The urban–suburban comparison further reveals that EV ownership in suburban areas gradually overtakes that in urban areas, with the gap widening over time. For ICEVs, ownership in suburban areas peaks later (around 2025) than in urban areas, which peak earlier at around 2023. Furthermore, by the end of the simulation period, the stock of ICEVs in suburban areas remains higher than its initial level.

5.1.3. EVCI diffusion

Fig. 10 illustrates the evolution of EVCI over the simulation period under the baseline scenario. Overall, PrCPs consistently dominate, with their quantity far exceeding that of PCSs—a trend consistent with real-

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[30] Information on Sinopec's vehicle market forecasts is available at: http://edri.sinopec.com/edri/news/com_news/20240109/news_20240109_325732006670.shtml.
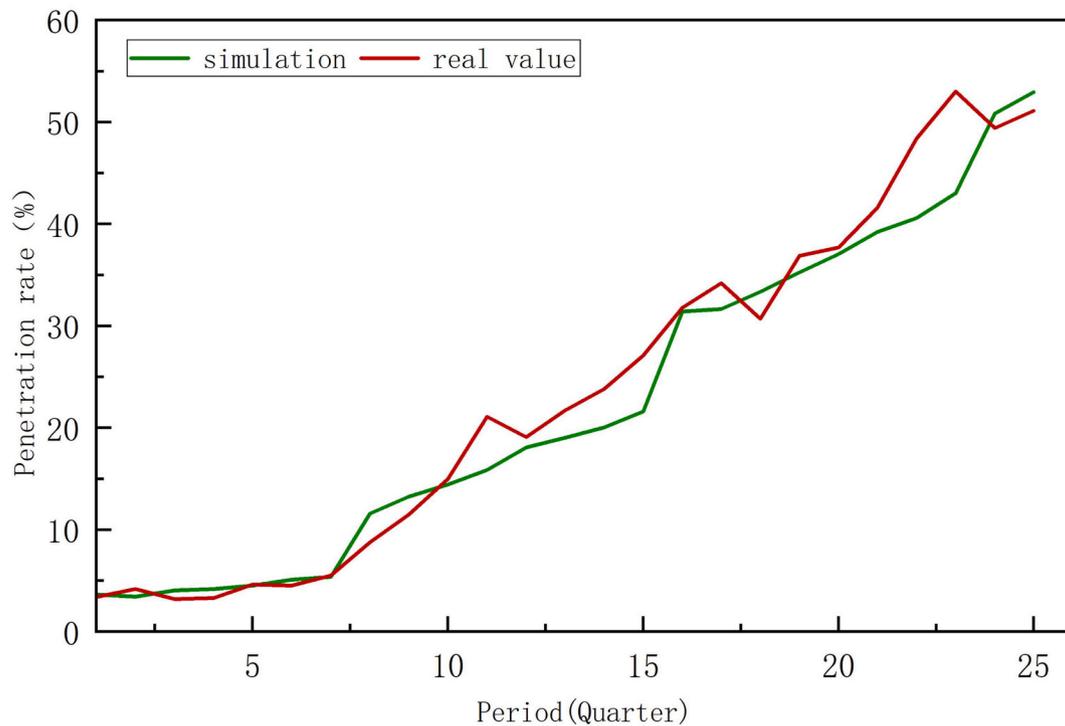
Fig. 4. Comparison of simulated and actual EV penetration rates.

world patterns of public and private charging infrastructure deployment.[31] As EV adoption expands in suburban areas, the number of PCSs in these regions eventually surpasses that in urban areas during the later stages of the simulation. However, in terms of spatial density, suburban areas maintain lower PCS density compared with urban areas throughout the entire simulation period.

5.1.4. EVCI operator profitability

Fig. 11 presents the temporal evolution of operating profits for EVCI operators. In the early stages, overall profitability remains low, with the operator in suburban areas even incurring negative net profits. This is primarily due to the immaturity of the EV market, where limited charging demand constrains revenue generation. Consequently, even with government subsidies, operating revenues are insufficient to cover costs, leading to financial losses in some cases. In contrast, operational performance in urban areas is relatively better, with OSs accounting for no more than 30 % of total profits. During the mid-to-late stages, as the number of EV users rises, operating profits grow rapidly. Suburban operators gradually surpass their urban counterparts in profitability, while the share of OSs in total profits gradually declines to approximately 17 % in both regions.[32]

5.1.5. Government subsidy expenditure

Fig. 12 illustrates the evolution of cumulative government subsidy expenditures over time. In the early and middle stages, cumulative spending on EVCI CSs is generally higher than that on OSs. However, in the mid-to-late stages, as EV penetration increases, cumulative OSs gradually surpass CSs. By the end of the simulation period, the total amount of OSs is about 3.85 times greater than that of CSs. This shift is primarily driven by the rapid growth in EV ownership during the later

stages, which leads to a substantial increase in charging demand and, consequently, subsidy spending tied to electricity usage. Additionally, the crossover points at which cumulative OSs exceed cumulative CSs occur earlier in urban areas compared to suburban areas.

5.2. Impact analysis of EVCI subsidies

To examine the impact of EVCI subsidies on the diffusion of EVs and charging infrastructure, a sensitivity analysis is conducted for both OSs and CSs. As summarized in Table 5, four alternative subsidy levels are specified in addition to the baseline scenario.

5.2.1. Effect of operational subsidy policies

5.2.1.1. EVCI quantity. Fig. 13 illustrates the impact of OSs on the number and proportional difference of PCPs over time. Among them, Fig. 13(a) shows the overall positive relationship between subsidy levels and PCP quantity. To better capture the temporal evolution of the effects, we also calculate the percentage difference in PCP quantity under each subsidy level relative to the baseline, which is obtained by dividing the difference in PCP quantity by the baseline quantity, as shown in Fig. 13(b). The results indicate that higher OSs stimulate greater PCS deployment in the early stages, with differences across subsidy levels remaining within 20 %. However, in the mid-to-late stages, the effect of OSs on PCP deployment gradually diminishes. One possible explanation is that during the early and middle stages, OSs significantly affect operator profits, which therefore shape ROI and infrastructure deployment decisions. As EV ownership increases substantially in the later stages, operator profits grow accordingly (see Fig. 11). Consequently, OSs become less critical in deployment decisions, and the differences across subsidy levels gradually converge toward zero.

5.2.1.2. EV ownership. The impact of changes in OSs on EV ownership is relatively modest. As shown in Fig. 14(b), the overall variation in EV stock remains within 4 %, which is significantly lower than the approximately 20 % variation in PCS deployment observed in Fig. 13(b). While the trajectory of EV ownership generally parallels that of charging
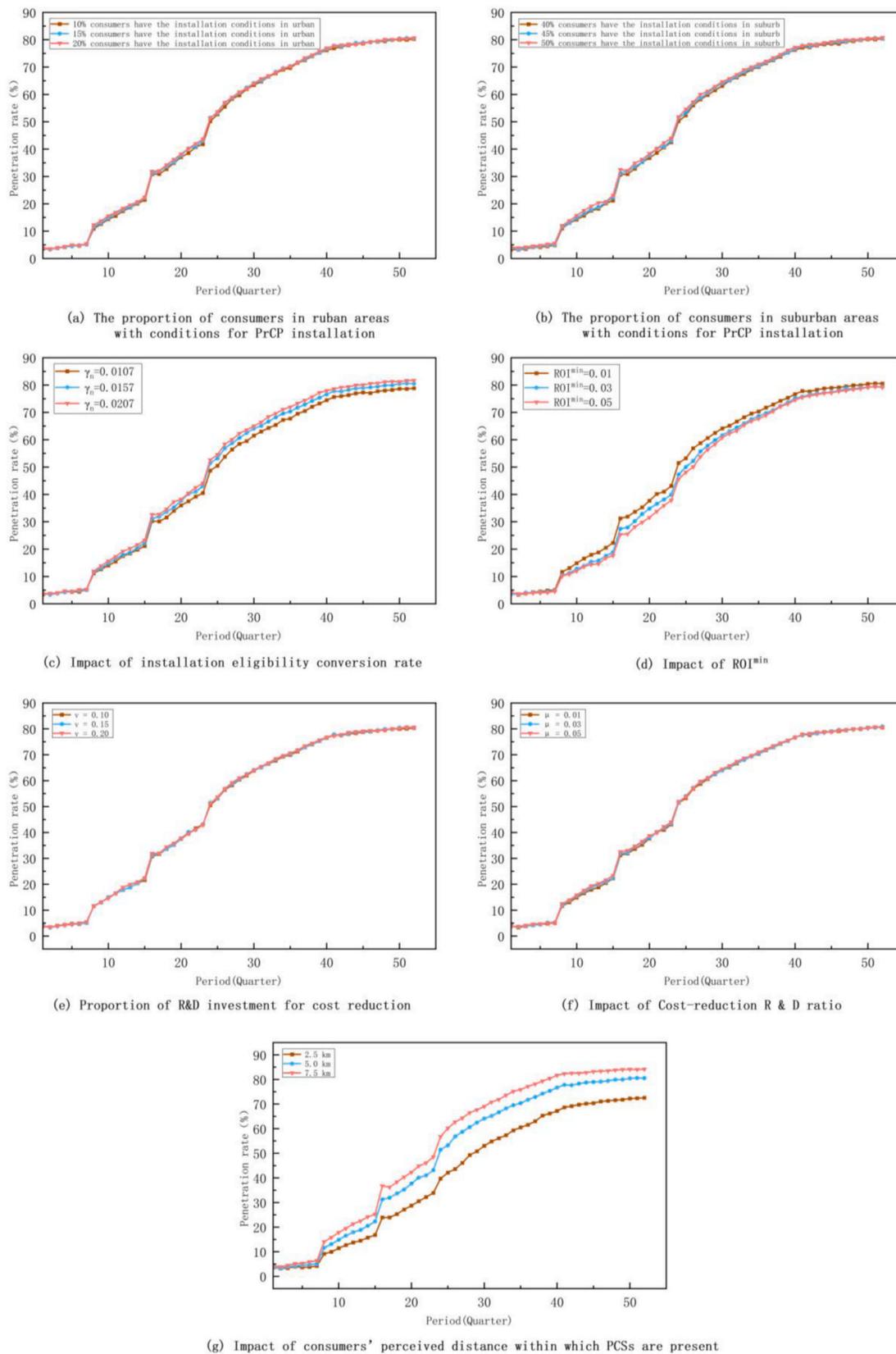
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[31] Real-world quantities of PCPs and PrCPs are available at: https://www.evcipa.org.cn/newsinfo/8137834.html.

[32] In Fig. 11, there are several periods where the OS-to-Profit ratio reaches 100 %, which correspond to cases in which the value of OS equals or exceeds the operator's net profit.

(a) The proportion of consumers in ruban areas
with conditions for PrCP installation

(b) The proportion of consumers in suburban areas
with conditions for PrCP installation

(c) Impact of installation eligibility conversion rate

(d) Impact of ROI^{min}

(e) Proportion of R&D investment for cost reduction

(f) Impact of Cost-reduction R & D ratio

(g) Impact of consumers' perceived distance within which PCSs are present

Fig. 5. Sensitivity analysis results based on EV penetration rate.
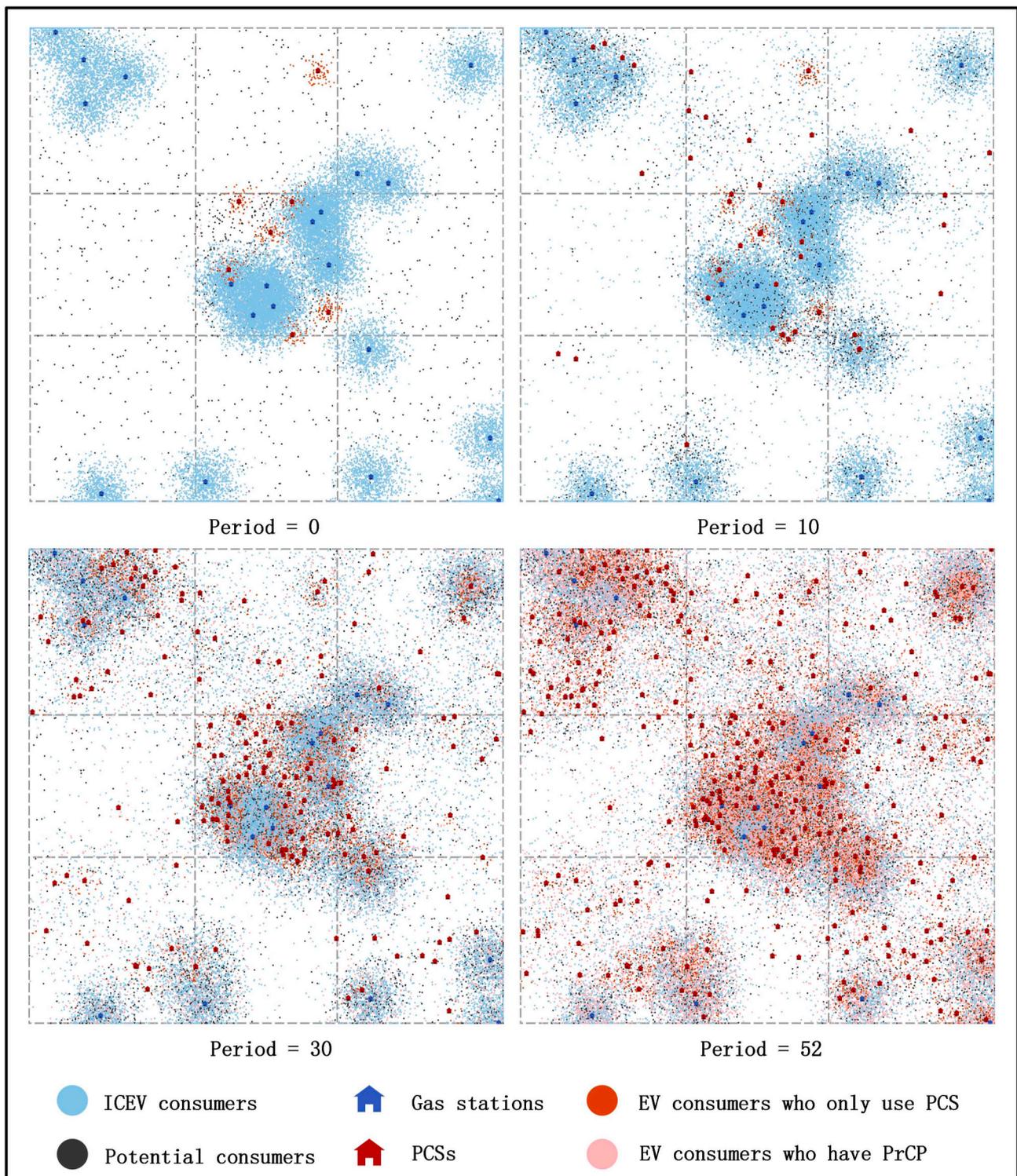
Fig. 6. Temporal spatial distribution under the baseline scenario.

infrastructure, it is worth noting that the peak difference in EV stock emerges with a noticeable time lag relative to PCS deployment. This lag arises because consumers begin to perceive changes in infrastructure availability once the number of PCSs surpasses a certain threshold, at which point EV ownership is influenced through the INE mechanism. These results provide indirect validation of both the existence and the role of INE in the EV diffusion process.

5.2.2. Effect of construction subsidy policies

Fig. 15(a) illustrates the impact of changes in CSs on the number of PCSs over time. In the early stages, higher CSs stimulate a significant increase in PCP deployment. However, as shown in Fig. 15(b), higher CSs are also associated with a noticeable decline in operator profitability. This counterintuitive outcome can be explained by the limited number of EV users during the early stages of market development. The overinvestment in PCPs, driven by the surge of CSs, dilutes the already low charging demand and limits the profitability of operators in the
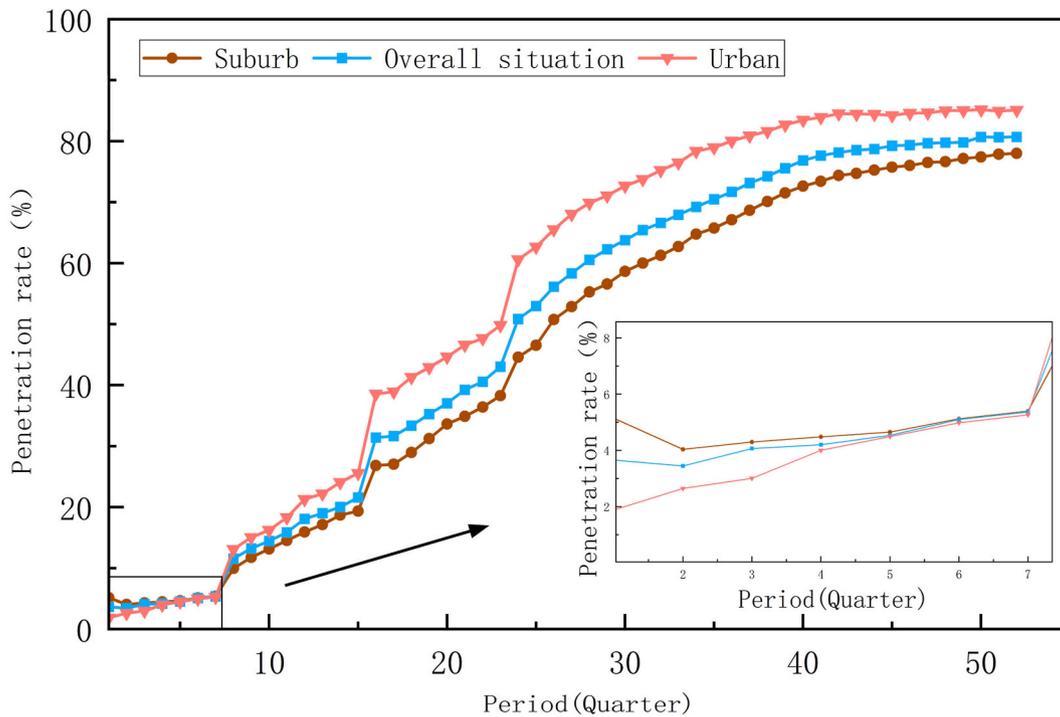
Fig. 7. Temporal evolution of EV penetration rate by region under baseline scenario.
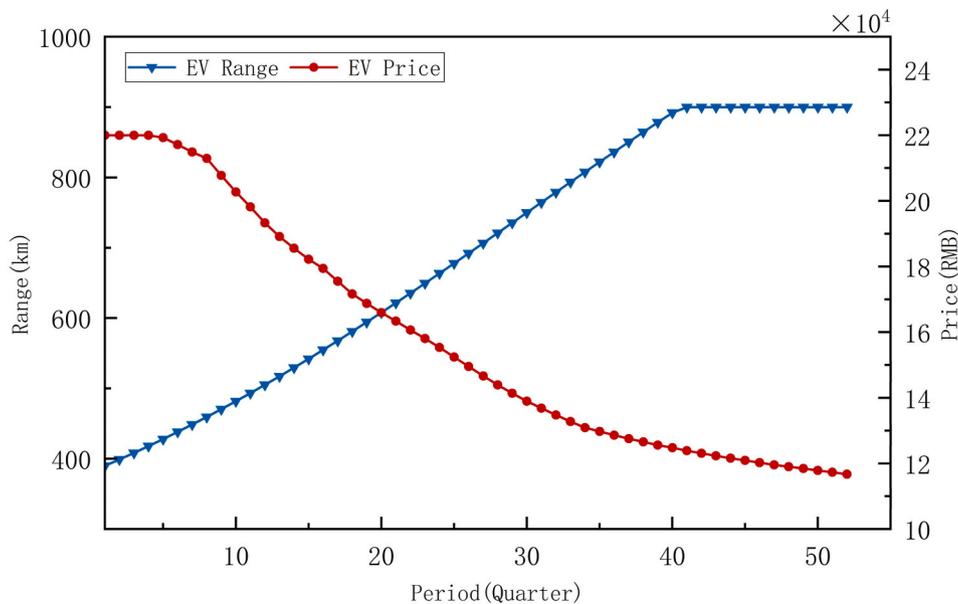

Fig. 8. Temporal evolution of EV purchase price and driving range.

short run. This phenomenon also sheds light on why many charging infrastructure providers in China experienced financial difficulties during the early stages of EV market expansion.[33] Faced with persistent operational losses, several charging infrastructure providers suspend services, resulting in the proliferation of so-called "zombie chargers", which refer to the inactive or non-functional PCSs that hinder EV diffusion. Introducing OSs during this stage can help alleviate the issue by incentivizing continued operation. Therefore, a policy shift from CSs

to OSs emerges as a necessary measure to promote the sustainable development of the charging infrastructure industry.

5.3. Impact analysis of subsidy phase-out policies

5.3.1. Setting for subsidy phase-out modes

Given the substantial fiscal burden associated with charging infrastructure subsidies, their gradual phase-out has become an inevitable policy trend. Indeed, many Chinese cities have already announced specific withdrawal plans. For example, Shanghai has outlined a two-stage reduction of OSs beginning in 2025, with a full termination scheduled by 2028. Hainan Province has retained CSs exclusively for

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[33] More details on this can be assessed at: https://report.iresearch.cn/report/202006/4456.shtml.
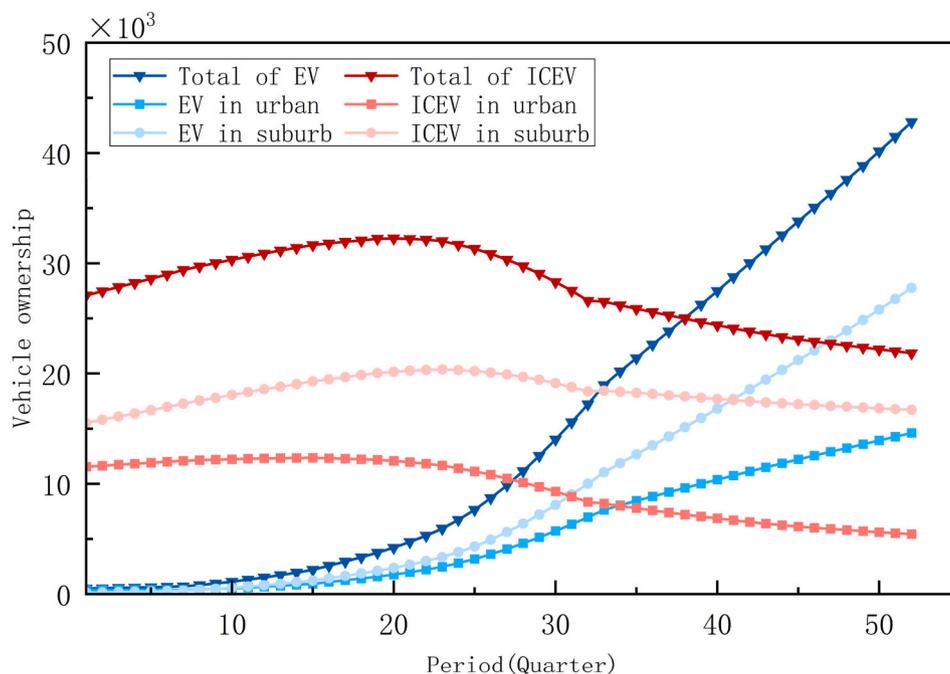
Fig. 9. Temporal evolution of vehicle market stock by type and region.
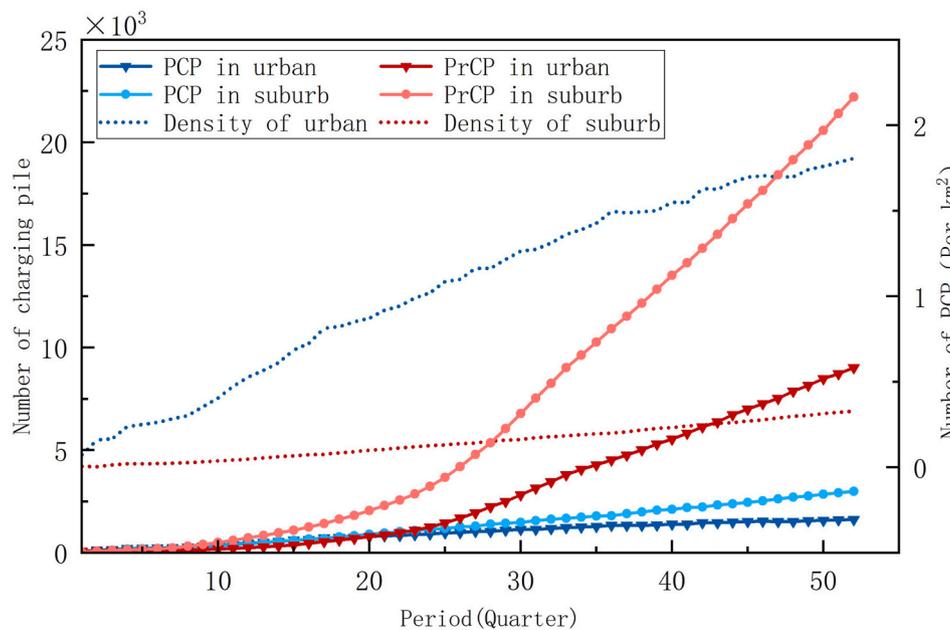

Fig. 10. Temporal evolution of EVCI scale and density by type and region.

rural areas, while lowering the subsidy rate from 10 %–15 % to 5 %–10 %. Similarly, Chongqing has announced that, beginning in 2026, its current OS of 0.1 RMB/kWh will be reduced by an additional 20 %, placing additional pressure on EVCI operators to enhance operational efficiency.

In the sensitivity analysis of EVCI subsidies, we find that their impact on the diffusion of EVs and EVCI is most pronounced in the early and middle stages of the simulation (before period 16). Building on this observation, and in line with real-world policy trends toward subsidy phase-outs, we design two alternative phase-out scenarios that begin in the middle stage (period 17), as summarized in Table 6. Mode 1 (gradual phase-out) assumes that subsidies are reduced by 25 % from their initial level starting in period 17, followed by additional 25 % reductions at

regular intervals until a full withdrawal is achieved by period 37. Mode 2 (rapid phase-out) assumes that subsidies are immediately halved in period 17 and fully eliminated by period 33.

To further investigate the effects of different initial subsidy levels on EV adoption, EVCI deployment, and government expenditure, this paper adopts a policy-mix approach. Specifically, we combine multiple initial levels of CSs and OSs with the two previously defined phase-out strategies. By pairing the five CS levels and five OS levels listed in Table 5 with the two phase-out modes, a total of 50 distinct policy combinations is yielded. For instance, *Policy Combination 1* (0.05, 150) represents a scenario with an initial OS level of 0.05 RMB/kWh and a CS level of 150 RMB/kW, followed by a gradual phase-out. Similarly, *Policy Combination 2* (0.25, 250) represents another scenario with an initial OS level of 0.25
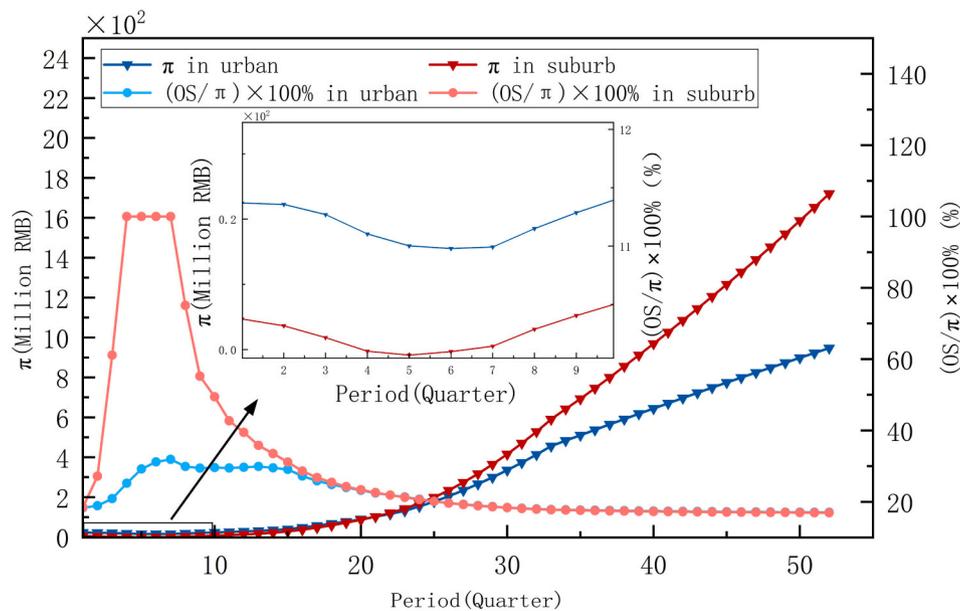
Fig. 11. Temporal evolution of EVCI operator profitability and OS-to-Profit ratio by region.
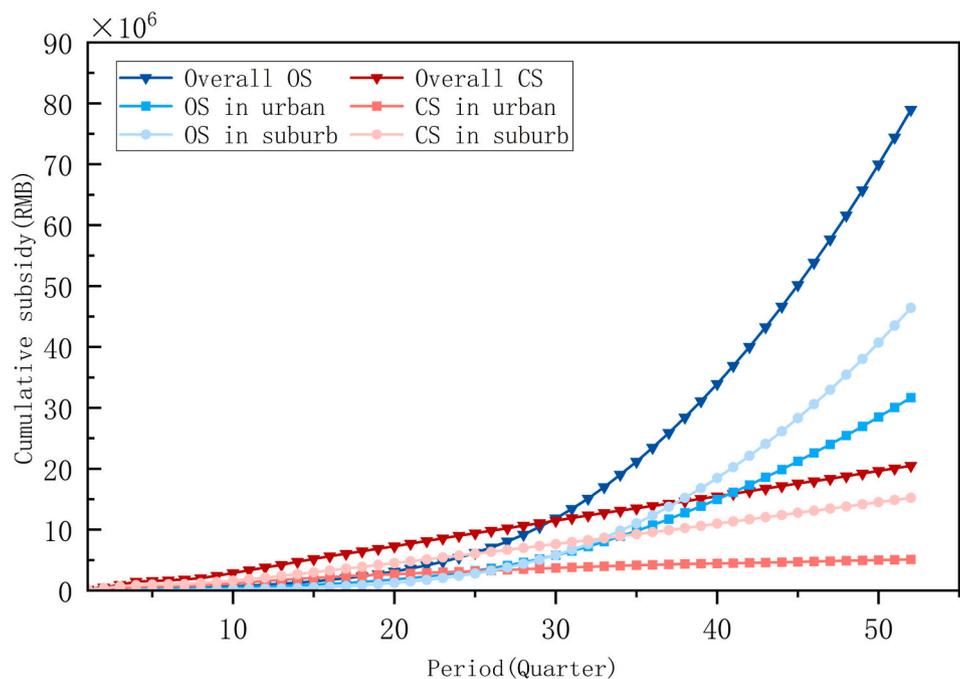

Fig. 12. Temporal evolution of cumulative subsidies by type and region.

Table 5
Specification of OS and CS levels.

Subsidy type	Level					Unit
	Very low	Low	Baseline	High	Very high	
OS	0.05	0.10	0.15	0.20	0.25	RMB/kWh
CS	50	100	150	200	250	RMB/kW

RMB/kWh and a CS level of 250 RMB/kW, under a gradual phase-out strategy as well. The following section provides a comparative analysis of outcomes across all 50 policy combinations.

5.3.2. Comparison of policy combinations

Fig. 16 presents the cumulative subsidy expenditure and EV stock levels at the end of the simulation period for each of the 50 policy combinations. Overall, the results indicate that, regardless of the phase-out mode, higher initial subsidy levels always lead to greater EV ownership. However, when comparing the two phase-out modes under identical initial subsidy configurations, the gradual phase-out mode results in significantly higher cumulative government spending, on average 22.30 % more than the rapid phase-out mode. By contrast, the corresponding increase in EV stocks is negligible, with an average difference of only 0.028 %.

To evaluate the efficiency of different subsidy phase-out strategies, which is defined as achieving higher EV adoption while minimizing
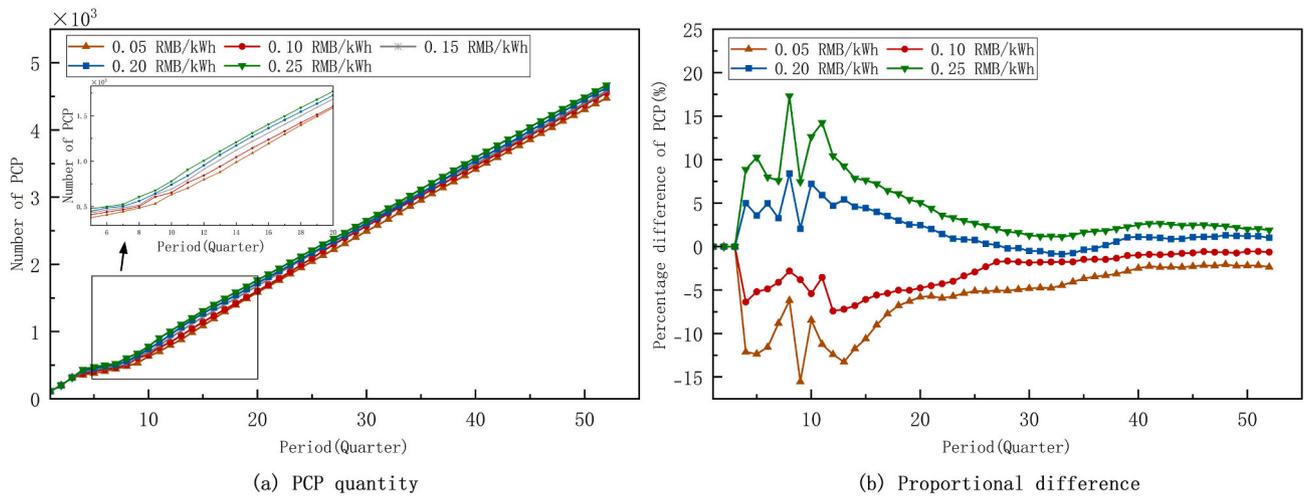
Fig. 13. Temporal evolution of PCP quantity and proportional difference by OS level.
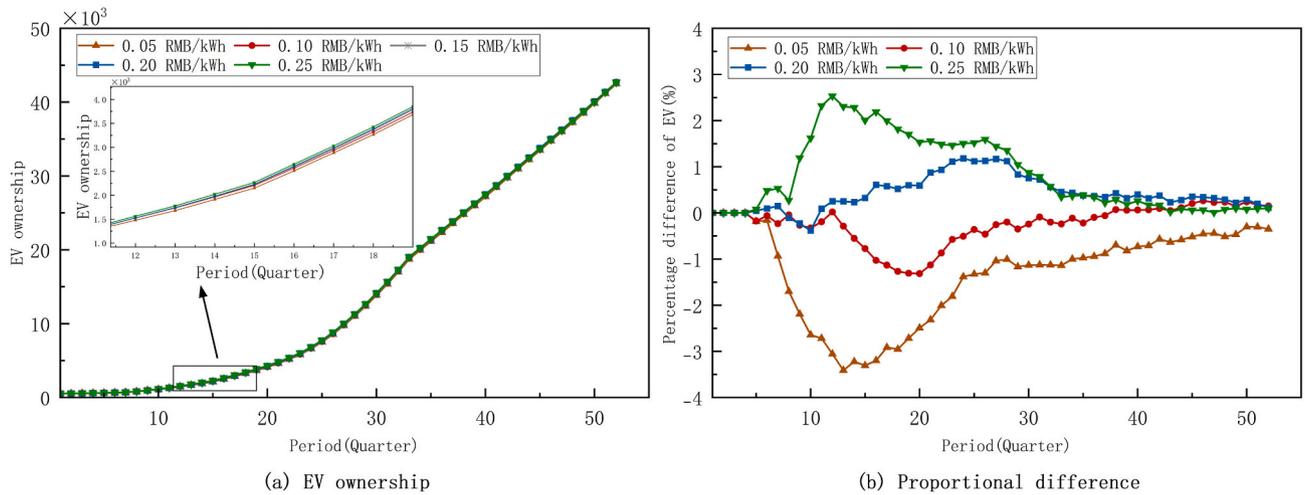
Fig. 14. Temporal evolution of EV ownership and proportional differences by OS level.
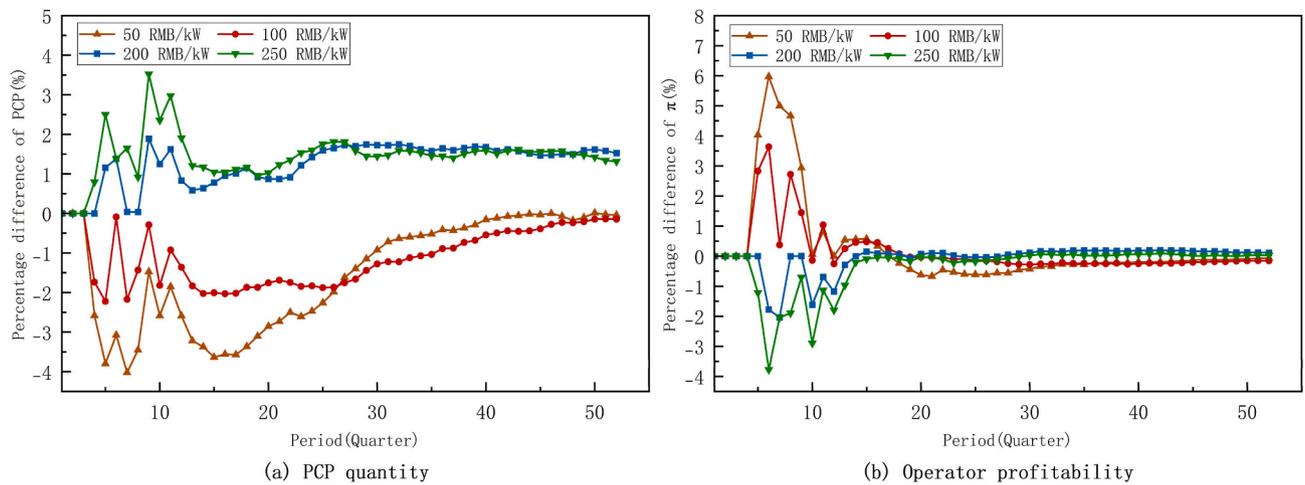
Fig. 15. Temporal evolution of PCP quantity and operator profitability percentage differences by CS level.

government expenditure, we conducted an additional analysis of the 50 policy combinations. The baseline subsidy level is defined as an OS of 0.15 RMB/kWh and a CS of 150 RMB/kW. Initial subsidy levels below this baseline are categorized as low subsidies, which include OS values of 0.05 RMB/kWh and 0.10 RMB/kWh, and CS values of 50 RMB/kW and 100 RMB/kW. Conversely, OS values of 0.20 RMB/kWh and 0.25

RMB/kWh, along with CS values of 200 RMB/kW and 250 RMB/kW, are classified as high subsidies. Under both phase-out modes, we focus on two distinct groups of policy combinations: (1) low OS with high CS, and (2) high OS with low CS. For ease of comparison, these combinations are plotted as connected points in Fig. 16. As shown in the figure, policy combinations with high initial OS and low initial CS cluster in the upper-left region of the graph, whereas those with low initial OS and high initial CS appear in the lower-right region. The comparative analysis reveals that, on average, combinations with high initial OC and low initial CS reduce cumulative government expenditure by 32.15 %, while simultaneously achieving 0.54 % higher EV ownership compared to the combinations with low initial OS and high initial CS. Taken together, these results suggest that policy combinations involving a rapid phase-out strategy with high initial OS and low initial CS are the most cost-effective.

5.3.3. Comparison of phase-out modes

Fig. 17 presents the EV stocks and EVCI quantities corresponding to each of the 50 subsidy phase-out policy combinations. For ease of comparison, two reference lines are added to indicate the levels of EV ownership and EVCI deployment under the baseline non-phase-out scenario (where baseline subsidy levels are maintained throughout the simulation). These reference lines divide the figure into four sub-regions. Policy combinations falling in the upper-right region result in increases in both EV adoption and EVCI deployment compared to the baseline. This indicates that, provided initial subsidy levels are relatively high, implementing a phase-out policy does not hinder the diffusion of EVs or charging infrastructure. However, it is also noteworthy that the gap in cumulative government spending between phase-out and non-phase-out policies is substantial. Compared with the baseline non-phase-out scenario, subsidy phase-out combinations reduce total government subsidy expenditure by 83.94 %–97.19 %. In other words, the upper-right region of Fig. 17 highlights a set of policy options that not only sustain or enhance EV adoption and EVCI deployment, but also dramatically alleviate fiscal burdens.

Specifically, we compare EV ownership and cumulative subsidy expenditure under the policy combination (0.15, 150) across both gradual and rapid phase-out scenarios, using the baseline non-phase-out scenario as a benchmark. Compared to the baseline, cumulative subsidy expenditures decrease by 90.07 % under the gradual phase-out and by 91.88 % under the rapid phase-out. Meanwhile, changes in EV ownership remain within 0.05 %, a difference that is practically negligible. These findings are consistent with our results in Section 5.1, which indicate that the impact of subsidies on EV diffusion is concentrated in the early and middle stages, with only limited effects observed in the later stages. If current subsidy levels were to be maintained throughout the entire simulation period, the rapid increase in EVCI deployment during the mid-to-late stages would result in substantially higher

Table 6
EVCI subsidy phase-out modes.

Period	Gradual subsidy phase-out (Mode 1)			Rapid subsidy phase-out (Mode 2)		
	OS	CS	Max OS	OS	CS	Max OS
[1,16]	Initial level		400 kW h/kW/ period	Initial level		400 kW h/kW/ period
[17,28]	Initial level*75 %		300 kW h/kW/ period	Initial level*50 %		200 kW h/kW/ period
[29,32]	Initial level*50 %		200 kW h/kW/ period	Initial level*25 %		100 kW h/kW/ period
[33,36]	Initial level*25 %		100 kW h/kW/ period	0	0	0
[37,52]	0	0	0	0	0	0

expenditures on both OSs and CSs. By contrast, the phase-out policies proposed in this study substantially reduce fiscal burdens without compromising the long-term diffusion of EVs.

5.4. Impact analysis of external factors

5.4.1. Gasoline and electricity prices

Fig. 18 illustrates the sensitivity of EV ownership to changes in gasoline and electricity prices. The results indicate that both factors significantly influence EV adoption decisions. As shown in Fig. 18(a), EV ownership is positively correlated with gasoline prices, while Fig. 18(b) illustrates a negative correlation between electricity prices and EV adoption. These findings are consistent with previous research, such as Luo et al. (2023) and Shafiei et al. (2012).

5.4.2. Electricity consumption per hundred kilometers

Fig. 19(a) shows the sensitivity analysis of EV ownership with respect to variations in electricity consumption per 100 km. Similar to electricity prices, EV ownership is negatively correlated with electricity consumption per 100 km, as both factors influence consumer purchase decisions through their effect on the driving cost of EVs. Meanwhile, as shown in Fig. 19(b), lower electricity consumption per 100 km is associated with a reduction in the number of PCSs. This occurs because improved energy efficiency reduces overall charging demand, thereby discouraging the further deployment of PCSs. In light of ongoing improvements in energy efficiency, the charging infrastructure industry should strategically shift its focus from simply expanding the number of facilities toward enhancing service quality. Such a transition would signal the emergence of a value-driven development phase, characterized by fewer but more efficiently operated charging facilities, rather than continued scale-oriented expansion.

6. Conclusions and implications

6.1. Conclusions

This paper examines the effects of EVCI subsidies and their phase-out in China within an ABM framework and yields three main conclusions:

(1) The Chinese EV market is projected to sustain rapid growth, with the penetration rate expected to reach 79.78 % by 2030. A notable trend is the accelerated diffusion of EVs in suburban areas, where EV ownership is anticipated to eventually surpass that of urban areas. In terms of charging infrastructure, PrCPs are expected to remain dominant, while government subsidies will continue to play a crucial role in supporting the expansion of public charging facilities. Although suburban areas initially lag behind urban areas in PCP deployment, they are expected to overtake urban levels as EV adoption grows, albeit at a lower spatial density. From a profitability perspective, suburban charging piles may incur financial losses in the early stages but are likely to yield higher long-term profits for operators than their urban counterparts.

(2) EVCI subsidies are found to be most effective in promoting EV diffusion during the early and middle stages, with their influence diminishing in the mid-to-late stages. Specifically, our results indicate that raising the OC level from the current 0.15 RMB/kWh to 0.25 RMB/kWh can enhance charging pile deployment by up to 20 % in the early and middle stages but yields only about a 2 % increase in the later stages. While CSs can facilitate early infrastructure expansion, they risk causing overinvestment and operational inefficiencies, which may undermine the long-term sustainability of the industry. If current subsidy levels were maintained without phase-out, annual government spending in 2030 would be approximately 4.14 times higher than in 2024. These findings underscore the importance of shifting from CSs to
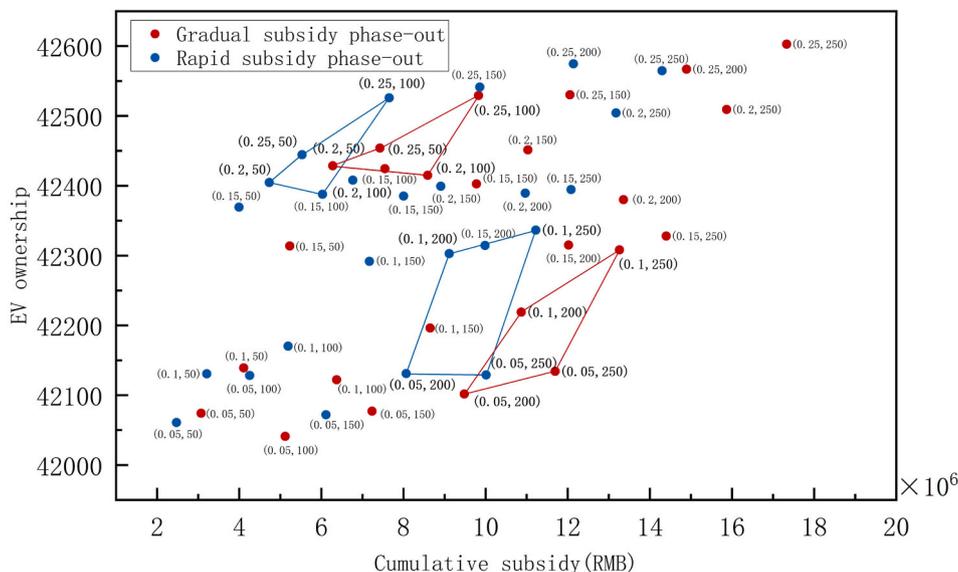
Fig. 16. Cumulative subsidy expenditure and EV ownership across policy combinations.
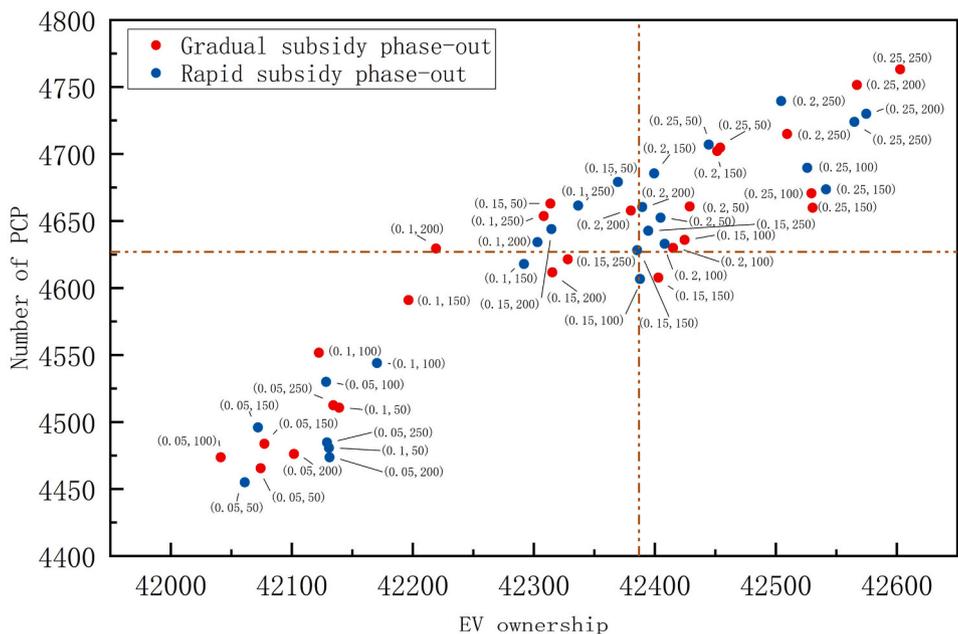

Fig. 17. Comparison of phase-out policy combinations and the baseline non-phase-out scenario.

OSs and adopting a phased reduction in subsidy policies in the later stages of market development.

(3) To assess the effectiveness of subsidy phase-out strategies, this study constructs 50 policy combinations by varying initial CS and OS levels across two phase-out modes. The simulation results indicate that maintaining current subsidy standards while adopting a phase-out mode can reduce cumulative government spending by 91 % compared to a no-phase-out scenario, while resulting in only a marginal 0.05 % decline in EV ownership. A comparison of the 50 policy combinations further reveals that, under identical initial CS and OS levels, the rapid phase-out mode reduces total expenditure by 22.30 % compared to the gradual mode. Moreover, a policy combination with high initial OS and low initial CS lowers cumulative expenditure by 32.15 % compared to the opposite setup (a combination with low initial OS and high initial CS). In summary, these findings suggest that

the most cost-effective policy mix consists of a rapid phase-out mode combined with high initial OS and low initial CS, as it significantly reduces fiscal expenditure without impeding EV diffusion.

6.2. Implications

Our findings provide insights for policymakers and generate practical guidance for EVCI operators. Based on the simulation results, the following specific recommendations are proposed:

(1) When designing subsidy policies, governments should account for the growing fiscal burden arising from rapid EV diffusion. In the early stages of market development, cities with adequate fiscal budgets and an urgent need to accelerate EV adoption may implement high levels of both CSs and OSs. Such a strategy
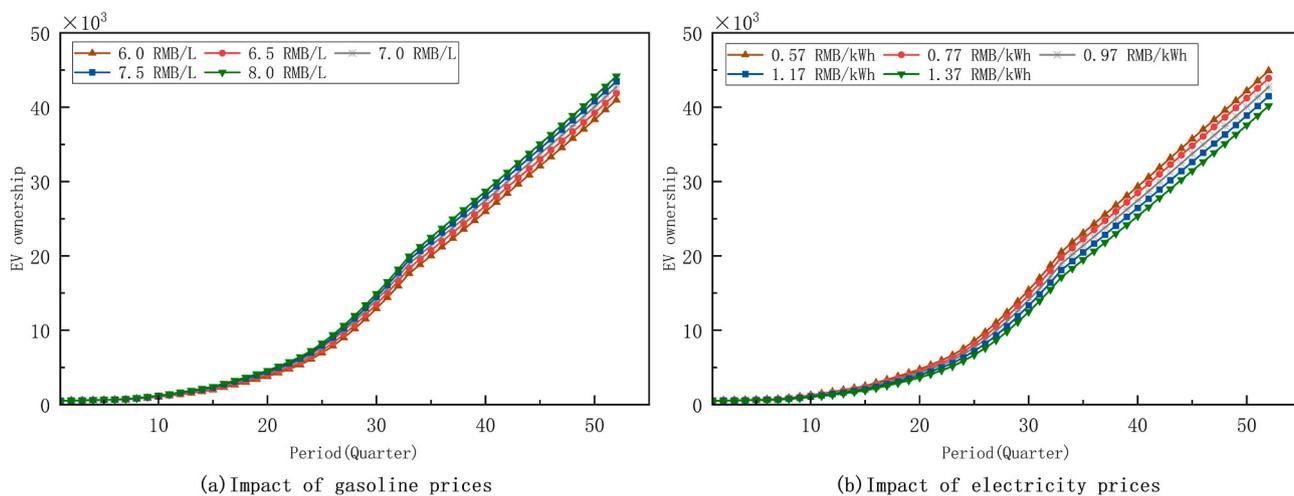
(a) Impact of gasoline prices

(b) Impact of electricity prices

Fig. 18. EV ownership under varying gasoline and electricity prices.

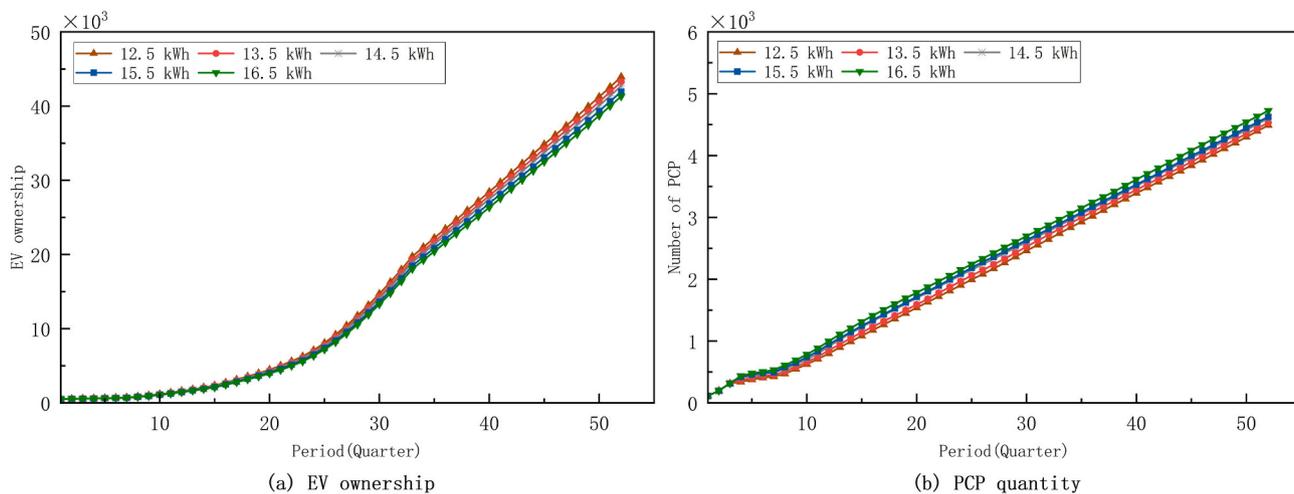(a) EV ownership

(b) PCP quantity

Fig. 19. EV ownership and PCP quantity under varying electricity consumption levels.

supports the rapid deployment of public charging infrastructure and helps operators overcome profitability challenges in the early stage. However, it is also essential to have strict supervision of CSs for the sake of efficiency in using public resources. Introducing capacity utilization assessments for operators can help prevent overinvestment in regions with limited charging demand. For cities facing tighter fiscal constraints, a strategy with relatively higher OS and lower CS, with a focus on enhancing operational performance, would be more appropriate. It is also recommended to link subsidy amounts to key performance indicators such as utilization rates and fault rates, which can facilitate the identification and elimination of underperforming charging stations. As the market develops, governments should adopt a dynamic subsidy phase-out mechanism that balances the reduction of subsidy expenditure and the promotion of EV diffusion.

(2) To promote balanced EVCI development across urban and suburban areas, policymakers should account for regional heterogeneity and adopt targeted measures. In terms of subsidy policy design, greater financial support should be allocated to suburban EVCI to accelerate infrastructure deployment and enhance operator profitability during the early stages of market development. On the technical and planning aspects, the government can leverage the relative ease of PrCP installation in suburban areas

by expanding charging pile capacity and streamlining installation requirements. Such efforts would help address issues such as limited grid capacity and cumbersome approval processes that currently constrain PrCP expansion. Through these measures, policymakers can foster a suburban EVCI development mode centered on PrCPs, with PCSs playing a complementary role, thereby fully leveraging the potential of PrCPs while overcoming key barriers to EV and EVCI adoption in suburban areas.

(3) EVCI operators should take advantage of the current subsidy window by prioritizing charging pile deployment in high-potential suburban areas, leveraging high OS levels to offset financial losses in the early stages. At the same time, implementing dynamic pricing strategies can help enhance utilization rates of piles and mitigate the impact of future subsidy phase-outs. Beyond pricing, operators should explore innovative business models to reduce operational and maintenance costs in suburban areas. For example, given the widespread presence of PrCPs in suburban areas, operators could collaborate with homeowners to pilot shared charging schemes. Furthermore, considering the unique characteristics of suburban land ownership, a crowd-funded installation model, where homeowners provide space and EVCI operators contribute equipment and technical expertise, could be an effective solution.

6.3. Limitations and future work

This study is subject to several limitations. First, it remains challenging to accurately model variations in EVCI capacity due to the complexity of influencing factors and the heterogeneous composition of EVCI with different capacity levels. As a result, EVCI capacity in this study is set to be static (exogenous) rather than dynamically evolving. Future research could apply alternative forecasting approaches to better capture the dynamic evolution of charging pile capacity.

Second, the electricity consumption per 100 km of EV driving is also treated as an exogenous variable in this study because of the lack of reliable forecasting methods, and thus a sensitivity analysis was conducted in this study to partially address this limitation. In addition, this model treats EV charging time and ICEV attributes (such as energy consumption per 100 km of driving, driving range, and vehicle price) as static. This simplification may lead to either overestimation or underestimation of the long-term attractiveness of EVs. Future research could address this limitation by developing dynamic models for both EVs and ICEVs to improve accuracy and more closely reflect real-world technological progress and usage conditions.

Third, automobile manufacturers are not incorporated into the model due to its complexity, as the primary focus of this study is on EVCI. For the sake of simplification, this paper also follows previous studies by considering only a single operator without accounting for competition among multiple operators. Future research could address these limitations by incorporating automobile manufacturers and

introducing competitive mechanisms among multiple operators to more accurately reflect the evolution of the EV market in the real world.

CRediT authorship contribution statement

Lijing Zhu: Conceptualization, Methodology, Writing – original draft. **Runze Li:** Data curation, Methodology. **Jingzhou Wang:** Software, Validation. **Haibo Chen:** Data curation. **Ondrej Havran:** Writing – review & editing. **Wen-Long Shang:** Supervision, Writing – original draft.

Declaration of competing interest

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

Appendix A

Table A1
Sample characteristics of survey respondents

Variable	Category	Sample size	Percentage
Gender	Female	305	57.2 %
	Male	228	42.8 %
Age	18–24	78	14.6 %
	25–34	244	45.8 %
	35–44	162	30.4 %
	45–54	37	6.9 %
	≥55	12	2.3 %
Income	<100,000 RMB	73	13.7 %
	100,000–150,000 RMB	154	28.9 %
	150,000–200,000 RMB	131	24.6 %
	200,000–300,000 RMB	109	20.4 %
	≥300,000 RMB	66	12.4 %
Place of residence	Central Urban area	261	49.0 %
	Inner suburban area	195	36.6 %
	Outer suburban area	30	5.6 %
	Rural area	47	8.8 %
EV ownership and PrCP installation status	Yes	173	32.5 %
	EV only	111	20.8 %
	No	249	46.7 %
PrCP charging time (PrCP + PCS) charging time	Not applicable	360	67.5 %
	≤20 %	14	2.6 %
	21–40 %	54	10.1 %
	41–60 %	51	9.6 %
	61–80 %	35	6.6 %
	>80	19	3.6 %
Vehicle purchase intention in the next year	Yes	385	72.2 %
	No	148	27.8 %
Annual driving mileage (unit: 10,000 km)	<1	64	12.0 %
	1–1.5	116	21.8 %
	1.5–2	250	46.9 %
	2–3	89	16.7 %
	≥3	14	2.6 %

Table A2
Income characteristics of respondents from different regions

Variable	Category	Sample size	Percentage
Income (Urban area)	<100,000 RMB	18	6.9 %
	100,000–150,000 RMB	57	21.9 %
	150,000–200,000 RMB	70	26.9 %
	200,000–300,000 RMB	68	26.2 %
	≥300,000 RMB	47	18.1 %
Income (Suburban and rural areas)	<100,000 RMB	52	19.0 %
	100,000–150,000 RMB	98	35.9 %
	150,000–200,000 RMB	63	23.1 %
	200,000–300,000 RMB	41	15.0 %
	≥300,000 RMB	19	7.0 %

Table A3
Geographic Distribution of the Responses

Province	Sample size	Province	Sample size
Beijing	29	Hubei	32
Tianjin	10	Hunan	15
Hebei	32	Guangdong	57
Shanxi	18	Guangxi	6
Inner Mongolia	7	Hainan	2
Liaoning	23	Chongqing	11
Jilin	7	Sichuan	19
Heilongjiang	8	Guizhou	16
Shanghai	23	Yunnan	9
Jiangsu	40	Shaanxi	13
Zhejiang	30	Gansu	8
Anhui	15	Qinghai	1
Fujian	25	Ningxia	2
Jiangxi	10	Xinjiang	2
Shandong	40	Henan	23

Table A4
Correlation matrix of demographic variables

	Income	Annual driving mileage	Minimum acceptable EV driving range	Maximum acceptable vehicle purchase price	Share of charging time at PrCP
Income	1				
Annual driving mileage	0.259***	1			
Minimum acceptable EV driving range	0.275***	0.106***	1		
Maximum acceptable vehicle purchase price	0.614***	0.242***	0.329***	1	
Share of charging time at PrCP	0.254***	0.176***	0.112***	0.306***	1

Notes: *p < 0.1; **p < 0.05; ***p < 0.01.

Appendix B

Table B1
Description of parameters and variables

Category	Symbol	Description	Symbol	Description
Parameters	P_f	ICEV purchase price	$P_{j,0}$	Initial purchase price of vehicle type j
	$R_{j,0}$	Initial driving range of vehicle type j	T_j	Refueling/recharging time for vehicle type j
	h_e	Electricity consumption per 100 km of driving for an EV	h_f	Fuel consumption per 100 km for an ICEV
	P_{elc}	Composite electricity price at a public charging station	P_{park}	Parking fee while charging
	P_{ser}	Service fee per unit (kWh) of electricity charged	P_{pri}	Charging price of private charging piles
	P_{gas}	Gasoline price	K_{pub}	Capacity of public charging station
	K_{pri}	Capacity of private charging station	σ_s	Share of charging volume in hour s
	n_j	Estimated service life of vehicle type j	$C_{ins,j}$	Insurance cost for vehicle type j per period
	$C_{mai,j}$	Maintenance cost for vehicle type j per period	θ	Inflection point of the technological maturity curve
	τ	Growth rate of the technological maturity curve	γ_d	Growth rate of licensed driver quality per period
	γ_n	Conversion rate of private charging pile installation eligibility per period	A_{ads}	Advertising income for a public charging station per period
	γ_c	Operating-to-construction cost ratio per period	C_{con}^{min}	Minimum construction cost for a charging station

Table B1 (*continued*)

Category	Symbol	Description	Symbol	Description
	z	Number of charging piles in a public charging station	s_{op}	Operational subsidy rate per unit of electricity charged
	s_{con}	Construction subsidy for each public charging station	$s_{op,max}$	Maximum subsidized charging volume per unit of charging pile capacity (kW)
Variables	E_{max}	Maximum charging volume for a station per period		
	$U_{i,j,t}$	Utility of user i from vehicle type j in period t	$P_{e,t}$	Purchase price of an EV in period t
	$Q_{j,t}$	Market stock of vehicle type j in period t	$R_{e,t}$	Driving range of an EV in period t
	$s_{pur,t}$	EV purchase subsidy in period t	$C_{dri,i,f}$	Cost per 100 km of driving for consumer i when using ICEV
	$C_{dri,i,e,pub}$	Cost per 100 km of driving for consumer i without private charging piles when using EV	$C_{dri,i,e,pri}$	Cost per 100 km of driving for consumer i with private charging piles when using EV
	$N_{i,j,t}$	Number of charging or gas stations within a 5-km radius of consumer i with vehicle type j in period t	B_i	Private charging piles access indicator (1 if yes, and 0 otherwise)
	y_i	Time of charging at PCS/(Time of charging at PCS + Time of charging at PrCP)	$Pr_{i,j,t}$	Purchase probability of vehicle type j in period t for consumer i
	$Tech_t$	Technological maturity of EVs in period t	ΔM_t	Newly added licensed drivers in period t
	M_t	Number of licensed drivers in period t	$M_{t,np}$	Number of consumers without private charging pile installation eligibility in period t
	π_t	Operating profit of EVCI operator in period t	E_i^c	Electricity demand of user i per period
	C_{op}^g	Operating cost for public charging station g per period	$N_{h,e,t}$	Number of public charging stations in region h in period t
	D_i	Driving distance of consumer i per period	C_{con}^g	Construction cost of public charging station g
	RD_t	R&D investment in period t	λ_t	R&D investment share of profit in period t
	μ	Share of R&D for cost reduction	ν	Effectiveness of R&D in lowering construction costs
	$C_{con,t}$	New public charging station construction cost in period t	$\Delta C_{con,t}$	Public charging station construction cost reduction in period t
	ROI_t	Rate of return for EVCI operator in period t	$\overline{\pi_t}$	Average operating profit for a public charging station in period t
	$S_{op,h,t}$	Amount of operational subsidy in region h in period t	$S_{op,t}$	Total amount of operational subsidy in period t
	$S_{con,t}$	Total amount of construction subsidy in period t	$\Delta N_{h,e,t}$	Number of newly built charging stations in region h in period t
	$\overline{r_t}$	Overall average utilization rate of public charging stations across the simulated region in period t	$\overline{r_{h,t}}$	Regional average utilization rate of public charging stations in region h in period t

Appendix C

Table C1
Consumer attribute settings

Parameter	Description	Value		Source
I	Annual income (unit: 10,000 RMB)	Urban area	Uniform [5,10), prob = 7 % Uniform [10,15), prob = 22 % Uniform [15,20), prob = 27 % Uniform [20,30), prob = 26 % Uniform [30,100], prob = 18 %	The survey study in Appendix A
		Suburban area	Uniform [5,10), prob = 19 % Uniform [10,15), prob = 36 % Uniform [15,20), prob = 23 % Uniform [20,30), prob = 15 % Uniform [30,100], prob = 7 %	
D_i	Driving distance of user i per period (unit: 1000 km)	Uniform [1.25,3.75] if I = [5,10) Uniform [2.50,5.00] if I = [10,15) Uniform [3.75,6.25] if I = [15,20) Uniform [4.375,6.875] if I = [20,30) Uniform [5.00,7.50] if I = [30,100]		The survey study in Appendix A
y_i	Proportion of user's total charging time at PCP	Uniform [0.6,0.8] if I = [5,10) Uniform [0.5,0.7] if I = [10,15) Uniform [0.4,0.6] if I = [15,20) Uniform [0.3,0.5] if I = [20,30) Uniform [0.2,0.4] if I = [30,100]		The survey study in Appendix A
P_{ke}	Maximum acceptable EV purchase price (unit: 10,000 RMB)	1.8 *I		a. The survey study in Appendix A b. (Sun et al., 2018)
P_{kf}	Maximum acceptable ICEV purchase price (unit: 10,000RMB)	1.4 *I		a. The survey study in Appendix A b. (Sun et al., 2018)
R_k	Minimum acceptable EV driving range (unit: km)	200 if I = [5,10) 350 if I = [10,15)		The survey study in Appendix A

Table C1 (*continued*)

Parameter	Description	Value	Source
P_{e0}/P_{f0}	Initial purchase price of EV/ICEV (unit: 10,000 RMB)	450 if I = [15,20] 550 if I = [20, 30] 650 if I = [30,100] 22/12	a. Closing the gap: the progress towards affordable EVs and the rising competition from China https://www.foglieviaggi.com/_/testi/jato_auto_report.pdf b. China's passenger car industry sales price, sales area and distribution of sales enterprises in 2019 https://www.chyxx.com/industry/202003/843866.html
R_{e0}/R_{f0}	Initial driving range of EV/ICEV (unit: km)	390/739	a. 2019 New Energy Vehicle Test Roundup: range & energy consumption chapter https://www.autohome.com.cn/drive/202001/962551.html b. The weighted average driving range of the top 10 best-selling ICEVs in 2019. Z. Wang (2020)
h_e	Electricity consumption per 100 km for EVs (unit: kWh)	14.5	
h_f	Fuel consumption per 100 km for ICEVs (unit: L)	6.5	Energy-saving and New Energy Vehicle Technology Roadmap 2.0 http://www.sae-china.org/news/society/202010/3957.html
T_e/T_f	EV recharge time/ICEV refuel time (unit: min)	90/5	a. 2019 China EV Charging Facilities Industry Development and Its Prospect Forecast Analysis Report https://www.iimedia.cn/c400/66231.html b. (Sun et al., 2018)
P_g	Gas price (unit: RMB/L)	7	https://data.eastmoney.com/cjsj/oil_default.html
n_e/n_f	EV/ICEV expected lifespan (in periods)	20/30	a. China New Energy Vehicle Usage Report 2024 https://www.autohome.com.cn/news/202412/1302716.html b. Possession Perspective: The Underlying Layout and Replacement Demand of China's Auto Market https://mp.weixin.qq.com/s/EQQJhpn_xQCGS3VH8bUxDQ
$R_{e,max}$	Maximum driving range of EVs (unit: km)	900	Energy-saving and New Energy Vehicle Technology Roadmap 2.0 http://www.sae-china.org/news/society/202010/3957.html
$C_{ins,e}$/$C_{ins,f}$	Insurance cost of EV/ICEV per period (unit: RMB)	1500/1000	https://www.d1ev.com/kol/93375
$C_{mai,e}$/$C_{mai,f}$	Maintenance cost of EV/ICEV per period (unit: RMB)	250/500	https://www.d1ev.com/kol/93375
ω	EV price learning rate	0.15	Luo et al. (2023)
$Tech_0$	Initial technological maturity of EV	0.5355	Shen et al. (2021)
τ	Growth rate of technological maturity curve	0.015363	Shen et al. (2021)
θ	Inflection point of technological maturity curve	658.73	Shen et al. (2021)
γ_n	Conversion rate of PrCP installation per period	0.0157	As calculated in this study
γ_d	Growth rate of licensed driver quality per period	0.01706	China's 2019–2024 automobile driver number growth rate https://www.mps.gov.cn/n2254314/n6409334/index.html

Table C2

Setting for EVCI operator attributes

Parameter	Description	Value	Source
P_{ser}	Service fee (unit: RMB/kWh)	0.6	How does China's charging service market develop healthily https://www.ev100online.com/research/detail/48
P_{park}	Parking fee per hour (unit: RMB/hour)	4	https://www.icauto.com.cn/tcw/
P_{elc}	Composite electricity rate at PCS (unit: RMB/kWh)	0.97	2022 White Paper on Charging Behavior of Electric Vehicle Users in China https://www.evcipa.org.cn/newsinfo/8137317.html
P_{pri}	Charging fee of PrCP (unit: RMB/kWh)	0.55	China combined meter tariff
K_{pub}	Charging capacity of PCP (unit: kW)	30	2019–2020 China Charging Infrastructure Development Report https://mp.weixin.qq.com/s/cOHUkUWx865Y3qM5qaK_eA
K_{pri}	Charging capacity of PrCP (unit: kW)	7	2019–2020 China Charging Infrastructure Development Report https://mp.weixin.qq.com/s/cOHUkUWx865Y3qM5qaK_eA
γ_c	Ratio of operational to construction cost	0.018	Hu et al. (2020)
A_{ads}	Advertising revenue for a single PCS per period (unit: RMB)	125	How does China's charging service market develop healthily https://www.ev100online.com/research/detail/48
λ_t	Proportion of profit allocated to R&D investment	0.1	2019 Financial Report of Jiangxi Firstar Panel Technology Co.,Ltd https://money.finance.sina.com.cn/corp/view/vCB_AllBulletinDetail.php?stockid=300256&id=7344483
μ	Cost-reduction R&D ratio	0.01	Assumption
ν	Effectiveness of R&D in cost reduction	0.25	Assumption
$C_{con,o}$	Initial construction cost for a single charging station (unit: 10,000 RMB)	57	a. 2019 China EV Charging Facilities Industry Development and Its Prospect Forecast Analysis Report https://www.iimedia.cn/c400/66231.html b. 20 kV and below distribution network engineering quota and cost calculation regulations https://zfxxgk.nea.gov.cn/2023-03/02/c_1310702541.htm
C_{con}^{min}	Minimum construction cost for a single charging station (unit: 10,000 RMB)	42	Based on the field investigation
ROI^{min}	Minimum acceptable ROI for EVCI operator	0.01	Based on the field investigation
s_{op}	EVCI OS standard for a single PCP (unit: RMB/kWh)	0.15	The subsidy policy in China
s_{con}	CS for a single PCP (unit: RMB/kW)	150	The subsidy policy in China

Table C2 (*continued*)

Parameter	Description	Value	Source
$s_{pur,t}$	EV purchase subsidy (unit: RMB)	Table 4	The subsidy policy in China
$s_{op,max}$	Maximum OS for a single PCP per period (unit: kWh/kW/period)[34]	400	The subsidy policy in China
z	Number of charging piles at a PCS	10	Based on the field investigation

[34] The maximum OS for a PCP within a specific period is determined based on its capacity and charging output. An example is the subsidy policy in Guangxi Province, where the annual subsidized charging volume is capped at 2000 kW h per kW for each charging pile. For a 30-kW charging pile in that case, its annual subsidy cap is calculated as: 30 kW *2000 kW h/kW/year = 60,000 kW h/year. In our study, we adjust the annual cap to 1600 kW h per kW. As the simulation is conducted on a quarterly basis, the annual cap is further converted into a per-period value of (1600 kW h/kW/year)/4 = 400 kW h/kW/period, accordingly.

Data availability

Data will be made available on request.

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