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Market potential of hydrogen fuel cell vehicles in Beijing: a spatial agent-based model approach

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Abstract
Hydrogen fuel cell vehicles (HFCVs) are vital for advancing the hydrogen economy and decarbonizing the transportation sector. However, research on HFCV market dynamics in passenger vehicles is limited, especially incorporating both market competition from other vehicle types and the comprehensive supply–demand market dynamics. To bridge this gap, our study proposed a spatial agent-based model to simulate the HFCV market evolution, with the aim of finding effective strategies and policy implications for breaking the diffusion dilemma of the HFCV market. We calibrated the model using survey data (N = 1065) collected from Beijing and evaluated its performance across five "What-If" scenarios. Results indicate that HFCVs and hydrogen stations are difficult to penetrate under the current conditions, despite HFCV applicants and market share growing by 37.5% and 15.63%, respectively. Consumer perceptions on cost, social and environment have greater impacts on HFCV proliferation than facility availability. The HFCV purchase subsidy has much greater impact than the technological learning rate, greatly accelerating its market emergence timing. Finally, HFCVs' diffusion significantly influences the market of battery electric vehicles.

Keywords Hydrogen fuel cell vehicle · Market evolution · Demand–supply dynamics · Spatial agent-based model · Policy analysis

Introduction

Global warming, environmental and energy issues are forcing industries to adopt cleaner, alternative energy sources to meet decarbonization targets (Li and Taghizadeh-Hesary 2022; Moon et al. 2022; Zhu et al. 2024; Waseem et al. 2025). In the transport sector, decarbonizing transport lies in how to get the general public to embrace and use cleaner vehicle technologies (Waseem et al. 2019; Huang et al. 2021; Ji et al. 2024). For this reason, the hydrogen economy has emerged, as a phenomenal economy, with cleaner energy alternatives and reductions in carbon emissions being achieved through the market proliferation of hydrogen fuel cell vehicles (HFCVs) (Harichandan and Kar 2023; Li et al. 2020). Specifi-

Extended author information available on the last page of the article cally, HFCVs operate by utilizing electricity generated from the chemical reaction between hydrogen and oxygen, producing water as a benign by-product instead of emitting harmful particulates and gases. The zero-emission nature of such vehicles is world-renowned, making them one of the mainstream mobility tools of the future (Harichandan and Kar 2023; Li et al. 2020; Waseem et al. 2023). However, compared to other vehicle types (such as BEVs), HFCVs face challenges such as higher costs, a lack of refuelling stations, and limited availability of green hydrogen. These shortcomings have hindered their popularity and led to a market diffusion dilemma, further exacerbated by the technology lock-in effect of BEVs. Therefore, how to incentivize the HFCV market and get potential users to embrace this new technology has become a real problem that needs to be addressed urgently.

HFCV market diffusion is essentially the result of the evolution of a complex system which requires a consideration of the effects of policy interventions, consumer preferences, hydrogen refuelling stations (HSs), vehicle competition and network influence. In this system, stakeholders include potential consumers, energy facility operators, vehicle manufactures and the government, each making decisions in their own best interests, all of which together form a complex market environment. Fortunately, such a system is well suited for modelling with the agent-based model (ABM), which can further reveal the macro emergent effects of the micro factors in the system (Zsifkovits and Günther 2015; Guo et al. 2022; Liu et al. 2025a). It is noteworthy that ABM is widely used in the electric vehicle (EV) diffusion field, becoming increasing popular and are regarded as the most promising tool for simulating complex adaptive systems (Huang et al. 2021; Sica and Deflorio 2023; Liu et al. 2024). However, few existing studies have explored the evolution dynamics of HFCV market in the passenger transport sector, and the few studies that have explored the HFCV market potential have only empirically identified the key influences of HFCV adoption.

In response, our study proposed a bottom-up spatial ABM to simulate the evolution of the HFCV market in the passenger transport sector and thus reveal the supply–demand dynamics interaction behind it. Our model consists of potential consumers, vehicle manufacturers, energy facility operators, and the government, with the HFCV market evolution driven by the decision-making, negotiation, and interaction among these agents. The proposed model was applied to the city of Beijing, China, to evaluate its validity, and analysed in five "what-if" scenarios to gain some important practical insights. Noted that our model also considers the influence of other vehicle types, such as BEVs, plug-in hybrid electric vehicles (PHEVs), and conventional vehicles (CVs), as the adoption and diffusion of HFCVs in reality are inevitably affected by these vehicle markets. We aim to uncover the more realistic market diffusion patterns of HFCVs, identify effective intervention strategies, and explore how to facilitate the transition from other vehicle markets to the HFCV market. Our study is also novel in two aspects. First, we proposed a bottom-up spatial ABM framework that can explore the evolutionary patterns of the HFCV market and quantitatively assess impacts of different factors. Second, the model is essentially a complete supply–demand dynamics model, integrating the impact of the market evolution of CSs and HSs.

Literature review

The factors influencing the HFCV adoption

Identifying the key factors that influence potential users to purchase HFCVs has been at the forefront of vehicle adoption research and underpins the modelling of vehicle purchase behaviour. Car purchase decisions result from the combined influence of multiple factors, including economic, psychological, and social aspects, with price, brand, product features, and perceived value being the most significant (Phuong et al. 2020; Liu et al. 2025b). Recently, several researchers have conducted a literature review on factors influencing HFCV adoption (Wang et al. 2024), which, generally, can be grouped into five categories: cost, facility availability, social influence, environmental awareness, and demographic characteristics. For example, in response to barriers to HFCV adoption and diffusion, Hardman et al. (2017) identified five key barriers: the lack of hydrogen infrastructure, hydrogen sourcing issues, inability to refuel at home, cost concerns, and hydrogen safety issues. Rawat et al. (2024) added that technological barrier is the most significant barrier to the HFCV market in India, and that building hydrogen supply network and infrastructure, increasing consumer awareness, developing policies and more efficient production technologies were the basis for large-scale adoption of HFCVs.

Regarding the adoption behaviour by individuals, Khan et al. (2020) employed a discrete choice model to investigate the factors driving HFCV adoption when consumers had to choose among BEVs, PHEVs, HFCVs, and CVs. Their study highlighted that government incentives, such as free public parking and free public transport, played a pivotal role in shaping consumer preferences for HFCVs. Moreover, socio-demographic attributes, education levels, and the availability of apartment parking were found to significantly affect the adoption of HFCVs. Li et al. (2020) found that vehicle prices, cruising range, refuelling time, fuel cost, emission reduction, and refuelling convenience were important influences on the purchase of HFCVs in China. Khan et al. (2021) observed that potential early adopters of HFCVs in Japan exhibited similar patterns across factors such as gender, employment status, household size, weekly travel distance, and frequency of expressway use, all of which influenced their adoption decisions. Moon et al. (2021) classified early adopters into six categories and found that 44.9% people viewed HFCV as a potential option, including "Innovative luxury consumer group (6.2%)", "Advanced eco-friendly consumer group (12.6%)" and "Economy-oriented eco-friendly consumer group (26.1%)". Loengbudnark et al. (2022) conducted a usrvey in Australia to analyze factors of BEV and HFCV adoption and found that safety concerns had a greater impact on HFCV adoption than purchase costs and perceived benefits, and that apartment dwells preferred HFCVs. Moon et al. (2022) used a discrete choice model to examine the impact of technologies, government policies and consumer pereceptions on HFCV adoption and further analyzed the impact on HFCV market diffusion based on these preferences. Applying Maslow's hierarchical needs model, Harichandan and Kar (2023) analyzed what intrinsic needs motivate users to adopt HFCVs, and found that openness to experience, social influence, environmental concerns and esteem needs played key roles in adopting HFCVs in India. They suggested that the manufactures needs to justify the HFCV price and the government set a cap on the HFCV price.

Analysis and modelling of the HFCV market evolution

HFCV market modelling has been evolving theoretically and was proposed early by Collantes (2007), who argued that the success of a market for HFCVs depends on technological processes (e.g., on-board hydrogen storage and fuel cell durability), techno-economics (e.g., production learning, production volume, accessibility to hydrogen fuel dispensing stations, the cost of hydrogen fuel, and R&D investment and etc.), consumer behaviour (e.g., vehicle cost, perceptions on hydrogen safety, value proposition of HFCVs to CVs and social pressures), regulations and policy agendas. This summary is very comprehensive, in other words, the HFCV market is driven by a combination of supply- and demand-side markets and the policy environment. With this, we can also summaries the stakeholders involved in the HFCV market, including the government, vehicle manufacturers, HS operators, and consumers. On this topic, we refer the interested reader to the latest literature review on methods and modelling by Gnann and Plötz (2015) and Keith et al. (2020).

Regarding modelling HFCV market evolution system, Schwoon (2006) used ABM to model the interdependent dynamic system of vehicle manufacturers, consumers, HSs and government, simulating possible diffusion paths of HFCVs and exploring the impact of taxation on technology choice. But theirs is a model-driven study that greatly simplifies the agent's decision logic and gives little consideration to policy constraints. Collantes (2007) and Jun et al. (2008) used epidemiological model and system dynamic model to simulate the market diffusion of HFCVs, PHEVs and CVs, respectively. Considering the actions of the whole market (consumers, vehicle manufacturers, energy station owners and policymakers) and their interactions, KELES et al. (2008) used system dynamics model to explore the market evolution patterns of HFCVs. Considering the complementary role of HFCVs and HSs, Meyer and Winebrake (2009) modelled this relationship using system dynamics to simulate the market evolution of HFCVs. Park et al. (2011) used the bass diffusion model and system dynamics model to construct an HFCV penetration forecasting model that considered the infrastructure and cost decrease effects. Given large uncertainty embedded in innovation resistance, Zsifkovits and Günther (2015) proposed an ABM framework incorporating multiple elements of innovation resistance to simulate their impact on the diffusion of HFCVs and HSs. Focusing on the interaction dynamics between the government, consumers and HSs, Li et al. (2021) explored the impact of dynamic subsidies for HSs on the evolution of the HFCV market using the ABM and experience weighted attraction learning algorithm. Zhang et al. (2024) analysed the market potential for HFCVs and its regional variations within different regions using a mixed methodology of realistic data and analytic hierarchy process.

Research aims and gaps

After the literature review, it is evident that research on factors influencing HFCV adoption remains in its early stages, far from fully capturing real adoption behaviour, and continues to evolve. From a simulation perspective, these factors can be summarized as vehicle cost, facility availability, social influence, environmental preference, and demographic characteristics. On the other hand, existing HFCV market modelling research primarily emphasizes heavy-duty vehicles, with limited focus on the passenger transport sector. Dominated by top-down approaches, such as system dynamics, Bass diffusion, and epidemic models, these studies often neglect consumers' micro-behavioural impacts and fail to capture emergent phenomena. While some studies employ ABM, they typically concentrate on demand-side modelling (e.g., discrete choice models) or market-driven dynamics, with insufficient attention to heterogeneous behaviours, policy constraints, and spatial effects. In response, our study proposed a bottom-up spatial ABM to simulate the HFCV market evolution in the passenger transport sector, which can be used to find effective policies to incentivize the HFCV market by revealing its supply–demand dynamics. The proposed model was applied to the city of Beijing, China, to evaluate its validity, with five "what-if" scenarios set up to gain some important practical insights. The results are useful for the policy design of HFCVs and HSs deployment and operations.

Methodology

Model framework

Figure 1 illustrates the analytical framework of our study for modelling the evolution of stakeholders' decisions and market interactions in the HFCV market. The model involves four types of agents: consumers, energy facility operators, vehicle manufacturers and the government, where consumers are the demand side and the other stakeholders collectively

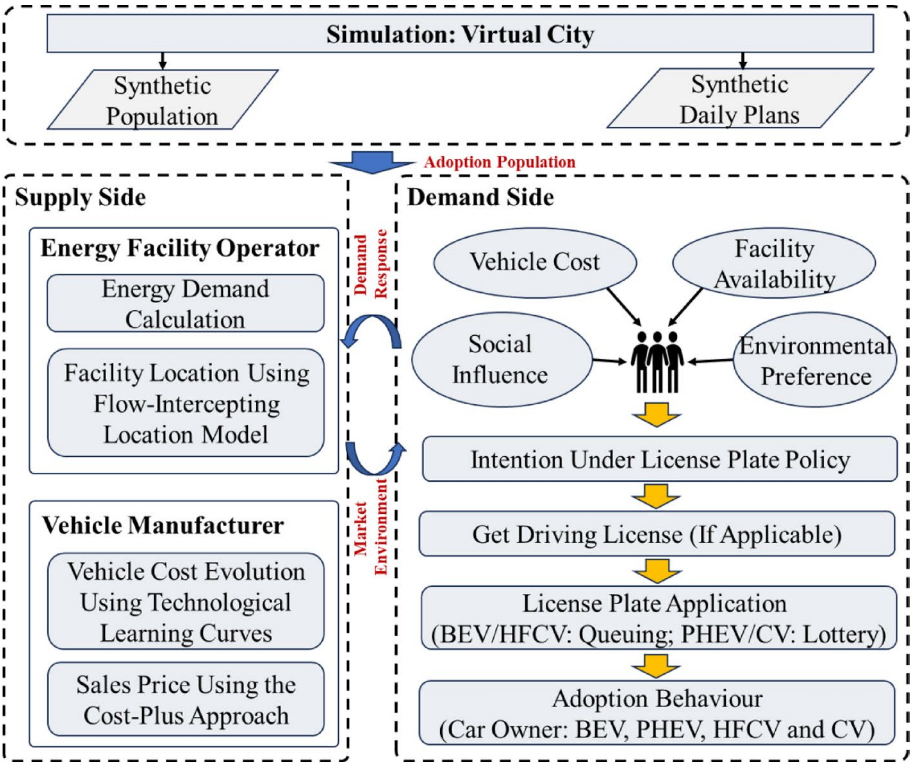


Fig. 1 The framework of agent-based HFCV diffusion model

form the supply side of car purchase services. Noted that the government functions as a supportive agent, regulating the vehicle market system through policy instruments such as HFCV subsidies. This exogenous approach enables us to evaluate the effectiveness of multiple policies. Given that the research framework exclusively addresses the interaction among decisive agents and lacks a specified decision-making behaviour for government agents, they have not been presented in Fig. 1. To avoid redundancy, the decision-making behaviours of consumer, energy facility operator, and vehicle manufacturer agents are detailed in Section "Agent-based vehicle market modelling considering demand and supply dynamics". Finally, the simulation model evolves in a virtual city that is an equivalent community of the real city, with everyone having demographic characteristics and daily plans (which contains activity and travel information).

Agent-based vehicle market modelling considering demand and supply dynamics

Consumer vehicle purchase decision

Consumers are the demand side of the vehicle market and typically have four options for purchasing a vehicle: BEV, PHEV, HFCV or CV. Vehicle purchase is an asset-heavy consumer behaviour, and for the general public, vehicle practicality and cost-effectiveness are the primary considerations (Schwoon 2006). To this end, we used four factors to portray the consumer's purchase utilities for different vehicles, including vehicle cost, facility availability, social influence and environmental preference (Zhuge et al. 2021, 2019), as shown in Eqs. (1)–(5).

$$U_{ij} = \alpha U_{ij}^{C} + \beta U_{ij}^{F} + \gamma U_{ij}^{S} + \delta U_{ij}^{E} \tag{1}$$

$$U_{ij}^{C} = -\frac{(p_j - sub_j)\,\varphi_{ij} - \min\limits_{k\in O_i}(p_k)}{\max\limits_{k\in O_i}(p_k) - \min\limits_{k\in O_i}(p_k)} \tag{2}$$

$$U_{ij}^{F} = f_{ij}\varphi_{ij} \tag{3}$$

$$U_{ij}^{S} = \frac{s_{ij}\varphi_{ij} - \min\limits_{k\in O_i}(s_{ik})}{\max\limits_{k\in O_i}(s_{ik}) - \min\limits_{k\in O_i}(s_{ik})} \tag{4}$$

$$U_{ij}^{E} = -\frac{e_j\varphi_{ij} - \min\limits_{k\in O_i}(e_k)}{\max\limits_{k\in O_i}(e_k) - \min\limits_{k\in O_i}(e_k)} \tag{5}$$

where U_{ij} refers to the total utility of purchasing vehicle j by consumer i; U_{ij}^{C}, U_{ij}^{F}, U_{ij}^{S} and U_{ij}^{E} denote sub-utilities of purchasing vehicle j by consumer i in terms of vehicle cost, facility availability, social influence and environmental preference, respectively; α, β, γ and δ are consumers' attitudes for each attribute in terms of importance in their decision-making. For each sub-utility calculation, we normalized each variable using the max–min normalization method, where φ_{ij} represents the adoption status of vehicle j by consumer i; p_j and e_j

are the selling price and carbon emission factor of vehicle j; sub_j is the vehicle purchase subsidy and the value is 0 for non-HFCV vehicles; f_{ij} and s_{ij} denotes the facility availability and social influence of consumer i with respect to vehicle j. If the facility is available, then $f_{ij} = 1$, else $f_{ij} = 0$. s_{ij} is calculated by $s_{ij} = adv_{ij} + nei_{ij} + 2 \cdot frd_{ij}$, where adv_{ij}, nei_{ij} and frd_{ij} are impact of advertisement, neighbour, and friendship, respectively.

Given the sustainability differences between CVs and EVs and urban congestion, policymakers generally favour EVs. Cities are also limited in the number of license plates they can issue each year. For example, Beijing requires a lottery to obtain a license plate for CVs and PHEVs, and a queue for HFCVs and BEVs. To this end, we firstly classify consumers' adoption intention into CVs or EVs according to the license plate policy, as shown in Eq. (6), where θ_{CVL} and θ_{EVL} is the ratio of CV and EV license plates published by the city each year. After knowing individual intention, they need to apply for a license plate. Here, we specifically assume that potential consumers may have a second choice, primarily for PHEVs and CVs, e.g., if an individual chooses HFCVs but his utility does not exceed the HFCV threshold, he is allowed to become a BEV applicant if his BEV utility exceeds the BEV threshold. We use $state_i$ to denote the vehicle application state of consumer i, as shown in Eq. (7), where $T_{bev}, T_{phev}, T_{hfcv}$ and T_{cv} are the vehicle adoption thresholds for consumers' BEV, PHEV, HFCV and CV.

$$Int_i = \begin{cases} \text{CV} & if\, true\ (\theta_{CVL}) \text{ and } \max U_{ij} = U_{i,cv} \\ \text{PHEV} & if\, true\ (\theta_{CVL}) \text{ and } \max U_{ij} = U_{i,phev} \\ \text{HFCV} & if\, true\ (\theta_{EVL}) \text{ and } \max U_{ij} = U_{i,hfcv} \\ \text{BEV} & if\, true\ (\theta_{EVL}) \text{ and } \max U_{ij} = U_{i,bev} \end{cases} \tag{6}$$

$$state_i = \begin{cases} \text{HFCV applicant} & if\, \text{int} = HFCV \text{ and } U_{i,hfcv} \geq T_{hfcv} \\ \text{BEV applicant} & if\, \text{int} = BEV \text{ and } U_{i,bev} > T_{bev} \\ \text{BEV applicant} & if\, \text{int} = HFCV \text{ and } U_{i,hfcv} < T_{hfcv} \\ \text{CV applicant} & if\, \text{int} = CV \text{ and } U_{i,cv} \geq T_{cv} \\ \text{CV applicant} & if\, \text{int} = PHEV \text{ and } U_{i,phev} < T_{phev} \\ \text{PHEV applicant} & if\, \text{int} = PHEV \text{ and } U_{i,phev} \geq T_{phev} \end{cases} \tag{7}$$

Energy facility location decisions

Energy facility operators need to deploy CSs and HSs to maximize profits while meeting vehicle owner refuelling needs as much as possible. The location of an energy facility determines the facility availability and influence consumers' vehicle purchase decisions. To this end, we used a flow-intercepting location model for energy facility location, and the relationships between vehicle owners and energy facility were also obtained. The location model was proposed by Berman et al. (1995), where demand is defined primarily by the flow on a predetermined route, usually the shortest path (O-D) between the origin and destination. Based on the daily plan of each agent, we first figured out all trip ODs and then calculated the traffic flows on all roads in the network to site CSs and HSs. The location model is shown in Eqs. (8)-(12).

$$\text{Max} \quad \sum_{p \in P} f_p x_p \tag{8}$$

$$\text{s.t.} \quad \sum_{i \in V} y_i = m \tag{9}$$

$$\sum_{i \in V_p} y_i \geq x_p, \forall p \in P \tag{10}$$

$$x_p = \{0, 1\}, \forall p \in P \tag{11}$$

$$y_i = \{0, 1\}, \forall i \in V \tag{12}$$

where, Eq. (8) expresses the maximisation of the intercepted flow; Eq. (9) imposes the number of facilities that have to be placed; Eq. (10) is consistency constraints between the two kinds of variables; x_p is the decision variable indicating at least one facility is located on path p; y_i is the decision variable indicating a facility is located at node i. Besides, V is set of nodes in the network; P is set of paths from O-D that are selected in the network; V_p is set of nodes that within the path p; F_p is the flow of path p; m is the number of facilities to be located. For ease of calculation, we assume that the HSs serve the same number of vehicles as the CSs, and that the number of stations needed is $m = \frac{D_j}{VP_{ratio} \cdot PS_{ratio}}$, where D_j is the number of vehicles using energy j, VP_{ratio} is the vehicle-to-pile ratio, and PS_{ratio} is the pile-to-station ratio.

Vehicle manufacturer pricing decisions

Manufacturers are primarily responsible for the price adjustment of vehicles, including BEVs, PHEVs, HFCVs and CVs, and its decisions significantly influence the vehicle purchase decisions of potential consumers. Here, we mainly used the technology learning curve to portray the production cost reduction trend of vehicles, and the method is widely adopted by the research related to new energy vehicles (Huang et al. 2021, 2022b). Note that given the maturity of CV technology, we assume that the technological learning rate for CV is 0. The technological learning curve for other vehicles is shown in Eq. (13). For durable goods, profits are usually limited and can usually be expressed in a cost-plus approach, as shown in Eq. (14),

$$c_j\left(Q_j\right) = c_{j0}\left(\frac{Q_j}{Q_{j0}}\right)^{-\sigma_j} \tag{13}$$

$$p_j = (1 + \mu)\, c_j\left(Q_j\right) \tag{14}$$

where $c_j\left(Q_j\right)$ is the production cost of vehicle j when its cumulative production volume is Q_j, c_{j0} is the cost of production when the initial production of vehicle j is Q_{j0}, σ_j is the parameter that reflects the technological learning ability of vehicle j, p_j is the sales price of vehicle j and μ is the profit margin on the sale of the vehicle.

Case study: analysis and results

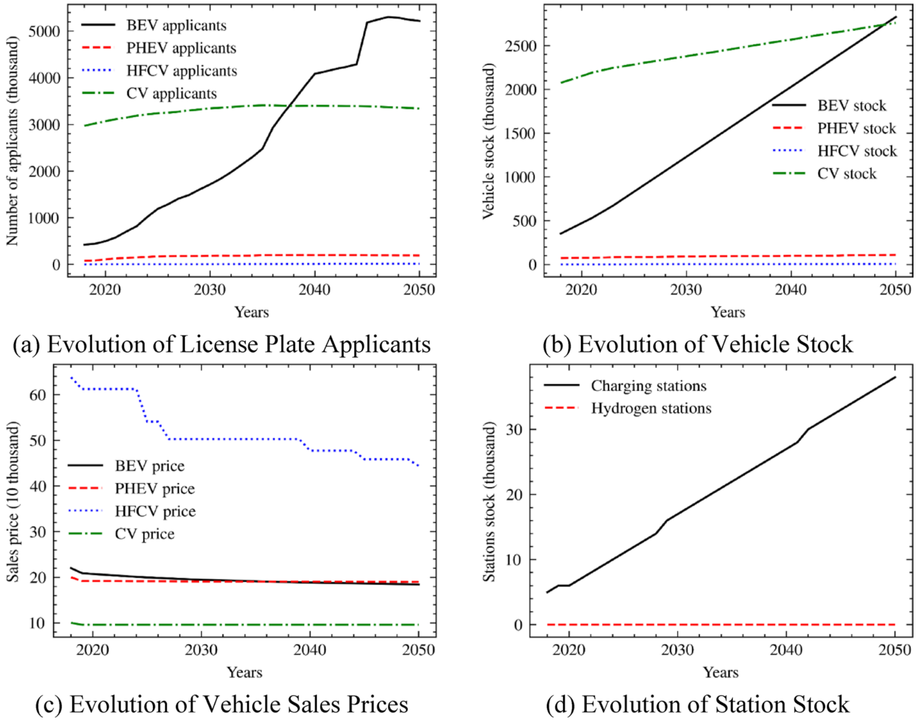
Model initialisation and calibration

We used Beijing, the capital of China, as the study area. Beijing is a core demonstration city for HFCVs in China (part of the Beijing-Tianjin-Hebei cluster), leading the nation in policy integration, technological innovation, and diverse application scenarios. Since the 2008 Olympics, Beijing has issued over 50 policies on hydrogen energy. Among them, the Beijing Hydrogen Energy Industry Development Implementation Plan (2021–2025), released in 2021, explicitly set a target of deploying over 10,000 HFCVs and building 74 hydrogen refuelling stations by 2025. The 2024 policy update added subsidies up to 5 million yuan for stations and tiered rewards for HFCV projects. In terms of achievements, Beijing's Daxing District has experienced the fastest development. By January 2025, it had 1,630 HFCVs, and by 2024, the Daxing International Hydrogen Energy Demonstration Zone had attracted 228 hydrogen energy companies. Additionally, Beijing regulates vehicle growth by issuing 100,000 passenger car license plate quotas annually, with 80,000 allocated to new energy vehicles—accessible via waiting lists or point-based rankings—and the remaining 20,000 for conventional vehicles, distributed through a lottery system. These attributes make Beijing a representative city for studying HFCV diffusion.

After determining the study area, obtaining the data required for the model initialisation and calibrating the model are the basis of a case study analysis. To this end, in terms of model initialization, we gathered data on the EV and charging market in Beijing, including market share, pricing, carbon emission factors, and charging station ratios. We surveyed 1065 citizens to synthesis the city's population and their travel plans, and obtained their vehicle preferences., We assumed the technological learning rates for HFCVs, estimated those for BEV and PHEV manufacturers using China's automobile production and sales data from 2018 to 2022, and derived the learning rate for CVs from existing literature (Huang et al. 2021). We gathered information issued by the Beijing government on the number of license plate issuances and the HFCV subsidies. Throughout the model initialization, we further validated the simulation model outputs, including population synthesis, travel plan synthesis, and historical outputs for various types of vehicles. They closely match the observed data with an acceptable margin of error. Further details on model initialization and calibration can be found in Appendix A of the supplement file.

Results of the baseline scenario

The baseline scenario reflects the existing vehicle market, and its simulated results are an expanded extension of the existing vehicle market with the assumption that the market would evolve as before. HFCV is allowed to be introduced in to the market in 2018. We first analysed the natural growth of the calibrated model, including the evolutionary trends of license plate applicants, vehicle market stock, vehicle sales prices and the number of HSs and CSs, as shown in Fig. 2. Subject to the license plate policy, the growth of vehicle market ownership in Beijing is relatively stable: BEV ownership increases from 0.353 million in 2018 to 2.832 million in 2050, with an average annual growth rate of 21.91%. PHEVs, HFCVs and CVs are growing at an average annual rate of 1.52%, 15.63% and 1.02%. This result is also reasonable, as about 60,000 of 100,000 annual license plates in Beijing are



(a) Evolution of License Plate Applicants

(b) Evolution of Vehicle Stock

(c) Evolution of Vehicle Sales Prices

(d) Evolution of Station Stock

Fig. 2 Results of baseline scenario about the vehicle market and fuelling stations

allocated to EVs and 40,000 are for CVs (Liu et al. 2022), and this tendency is further stretched, for example, Beijing has announced that 80% of the license plates were for EVs and 20% were for CVs in 2024.

In terms of vehicle applicants, the consumer vehicle preferences are even pro-environmental, and we could find that the average annual growth in applicants for HFCV licenses has been very fast (about 37.5%), followed by 35.52% for BEV applicants, 4.55% for PHEV applicants and 1.72% for CV applicants. It should be noted that although the growth rate of HFCV applicants is quite high, HFCV ownership is low, and therefore HFCV market share is low. Around 2038, the number of applicants for BEV licenses will exceed that of CVs. As for vehicle sales prices, from the highest to lowest, they are HFCVs, BEVs, PHEVs and CVs, with a general downward trend in prices. In terms of energy facilities, the number of CSs is growing significantly and increases from 5 in 2018 to 38 in 2050, with a 20.63% annual growth rate. However, due to the small base of HFCVs, their market holding is still small and fragmented, making it difficult for HSs to spread.

Figures 3 and 4 show the spatial distribution of the vehicle market and CSs for the years 2018, 2035 and 2050, respectively. Notably we do not map the spatial distribution of HFCVs and HSs because the diffusion dilemma of HFCVs has resulted in few HFCVs and HSs, e.g., only four HFCV users and no HSs by 2050. It can be found that the vehicles and infrastructures market are mainly concentrated in the six urban districts in the centre of Beijing, and spreads outwards from there, which is consistent with the real population distribution of Beijing (Liu et al. 2022; Zhuge et al. 2021). In the early years, BEVs were mainly accumu-

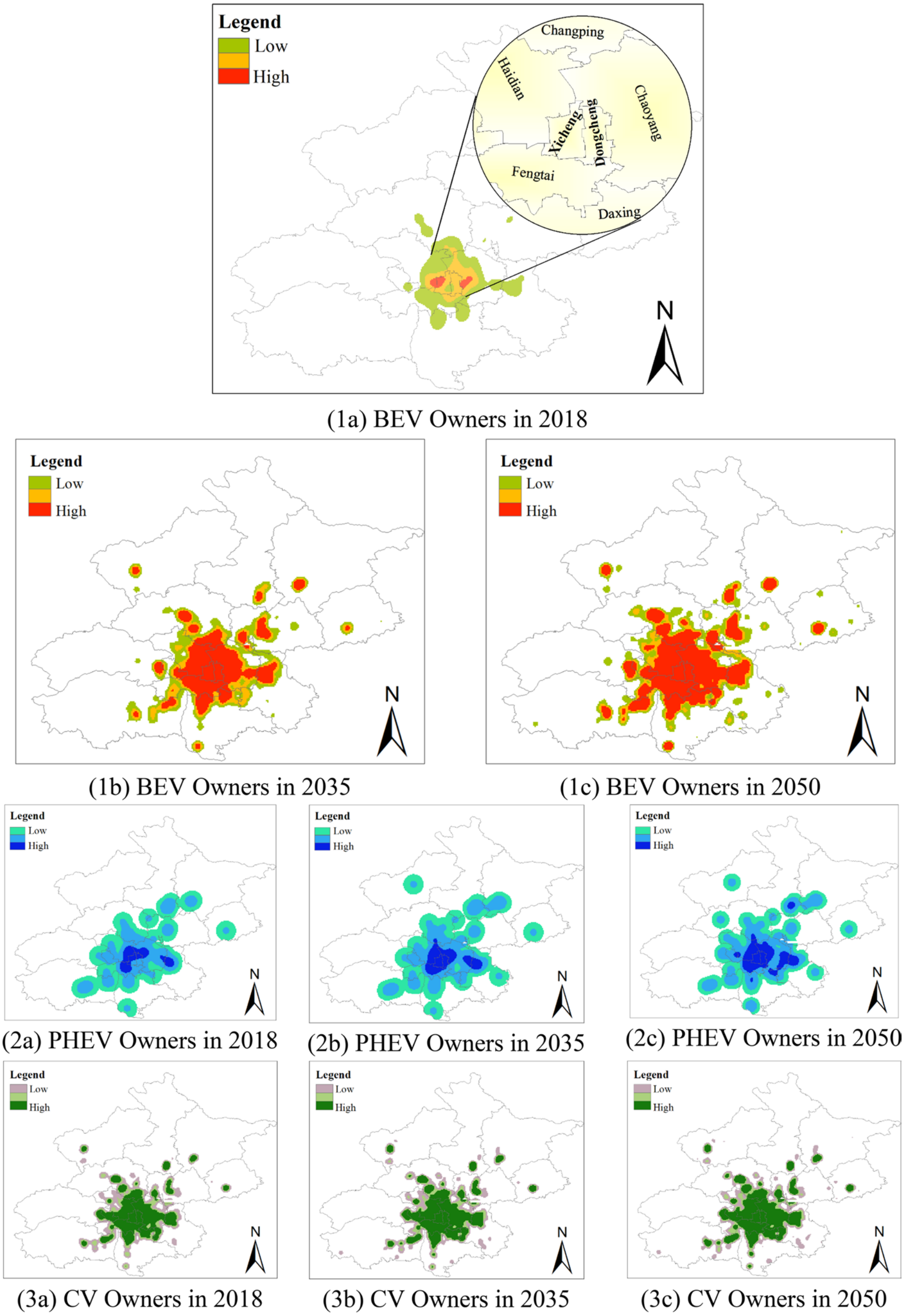
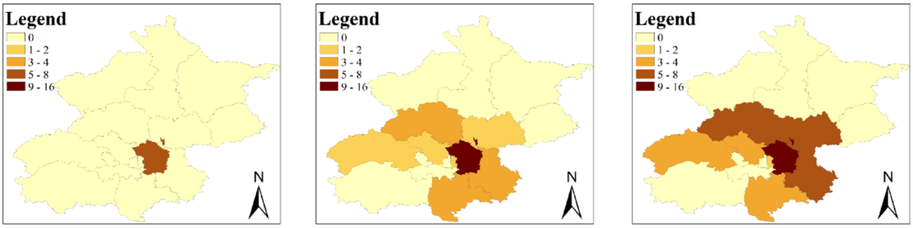


Fig. 3 Spatial distribution of BEV, PHEV and CV adopters based on residential locations in baseline scenario



(1a) CSs in 2018 (1b) CSs in 2035 (1c) CSs in 2050

Fig. 4 Spatial distributions of CSs from 2018 to 2050 in baseline scenario. (Note: the scaling factor of 1000 is applied in the simulation, and the layout of CSs here indicated their density only and does not represent their real locations (Unit: station/km^2))

lated in the Dongcheng and Chaoyang districts, which are the core districts of Beijing and the most economically developed areas. This trend is consistent with the spatial distribution of the proliferation of CSs, with early CSs concentrated in the Dongcheng and Chaoyang, and when the year 2050 rolls around the neighbouring urban districts.

Results of what-IF scenarios

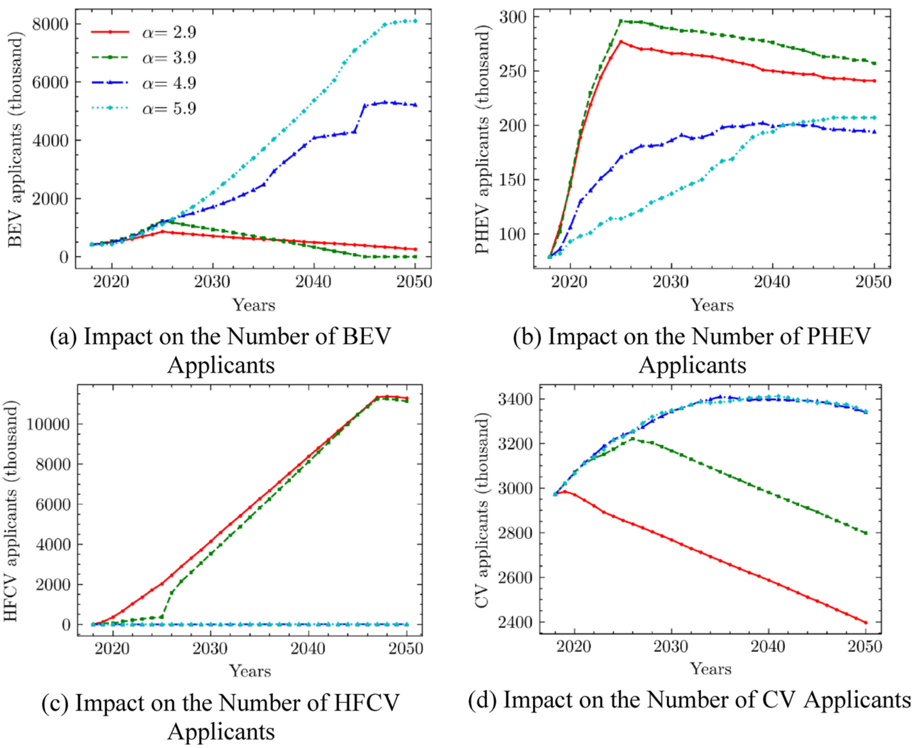
Baseline scenario indicates that HFCVs are difficult to break through the technological blockade of the existing market. To break out of this dilemma, we further proposed five what-if scenarios to explore potential strategies for promoting HFCVs. These scenarios include consumer preferences, purchase subsidies, adoption thresholds, technological learning rates and advertising.

Impacts of consumer preferences

There are four major individual preferences influencing vehicle purchase choices: vehicle cost, facility availability, social influence, and environmental preference. We began by exploring the impacts of these four factors to understand the influence of consumer-side preferences on the vehicle market evolution, and then derived effective managerial implications. Specifically, the consumer cost perception scenario explores how changes in consumers' emphasis on vehicle costs drive HFCV market formation, reflecting real situations like rising fuel prices or policy promotions making total costs a key purchase factor. The social influence scenario studies how interpersonal interactions and social networks affect HFCV diffusion, reflecting real cases where community promotions or public opinion guidance make consumers more susceptible to others' choices in vehicle purchases. The facility availability scenario explores how HFCV supporting infrastructure (e.g., HSs) coverage, density, and accessibility impact market diffusion, reflecting real efforts by governments or enterprises to build refuelling networks and subsidize infrastructure to enhance refuelling convenience. The environment preference scenario focuses on consumers' priority on vehicle environmental attributes and its impact on HFCV adoption, reflecting real situations where governments boost environmental awareness via campaigns, carbon credit policies, or "zero-emission vehicle" certifications to increase public interest in green transportation.

Regarding the perception on vehicle cost, this scenario analysed the extent to which consumers value vehicle cost when buying their vehicles. To this end, we test the vehicle cost perception value from 2.9 to 5.9 with an interval of 1 (parameter α in Eq. (1)) within the four simulation experiments, as shown in Fig. 5. It can be observed that the sudden decline in BEV and PHEV applicants around 2026 is due to a smaller cost perception coefficient (i.e., $\alpha = 2.9$ or 3.9), which leads more consumers to choose HFCVs over BEVs and PHEVs. This is because a smaller cost perception coefficient indicates that consumers place less emphasis on cost when purchasing a vehicle. As a result, factors such as the environmental friendliness and social benefits of HFCVs become the main reasons potential users are willing to purchase these vehicles, leading to a rapid decline in the number of applicants for BEVs and PHEVs. As the coefficient increases, the number of BEV and CV applicants increases and the number of PHEV and HFCV applicants decrease. This is easy to understand because consumer choice is divided into two categories—electric and petrol, and as consumers become more cost sensitive they favour older technologies, i.e., BEVs and CVs. For HFCVs, its market is more likely to emerge when consumers' perception on vehicle cost is below 3.9. This also means that lowering the sales price of HFCVs is key to incentivizing consumers to buy them, and is critical to the market diffusion of HFCVs.

Figure 6 illustrates the impact of social influence perception on consumer vehicle purchases from 2018 to 2050. Social influence perception refers to the extent to which consumers' vehicle purchase decisions are influenced by externalities, including friendship,



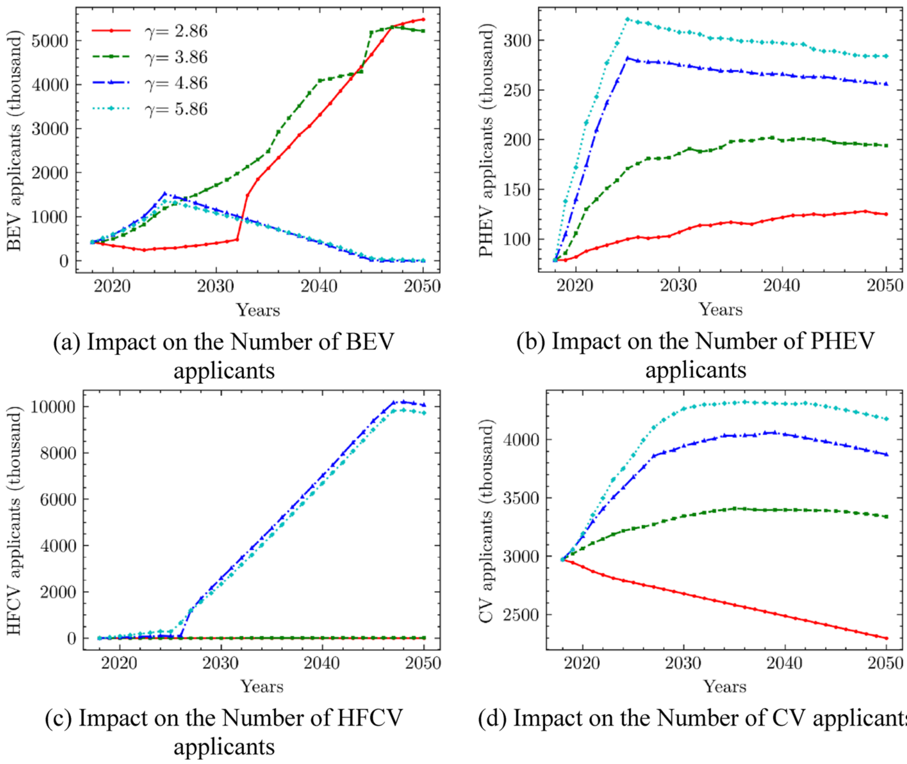
(a) Impact on the Number of BEV Applicants

(b) Impact on the Number of PHEV Applicants

(c) Impact on the Number of HFCV Applicants

(d) Impact on the Number of CV Applicants

Fig. 5 The vehicle market applicants expansion under different vehicle cost perception (the value is 4.9 in the baseline scenario)



(a) Impact on the Number of BEV applicants

(b) Impact on the Number of PHEV applicants

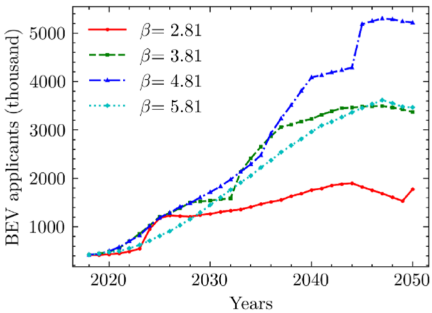
(c) Impact on the Number of HFCV applicants

(d) Impact on the Number of CV applicants

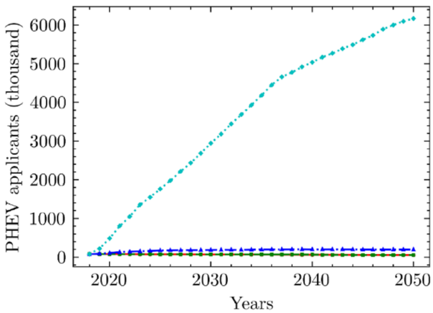
Fig. 6 The vehicle market applicants expansion under different social influence perception (the value is 3.86 in the baseline scenario)

neighbour, and advertising. In this scenario, we test the social influence perception value from 2.86 to 5.86 with an interval of 1 (parameter γ in Eq. (1)) within the four simulation experiments. When social influence perception increases, the more applicants look at opinions and influences from external sources when buying a car. With rising social influence perception, the number of BEV applicants first increases and then decreases, while others steadily grow. The current value of 3.86 shows BEVs are negatively impacted, others benefit, and HFCVs could achieve adoption by improving this perception. Noted that this conclusion does not imply questioning the sustainability of BEVs, as the current market perception of social influence is driving their rapid and steady growth. However, this result is also unexpected –both HFCVs and BEVs are clean vehicles, yet their social influence effects are completely opposite. This could be because as BEV adoption is already heavily influenced by social factors, an increase in social influence perception shifts priority to PHEV and CV, causing BEV adoption to decline rapidly. Conversely, HFCV decisions, being less affected by social influence, gain greater utility under higher social influence perception, leading to a swift rise in HFCV adoption. When social influence perception increases from 3.86 to 5.86 in 2050, the number of PHEV, HFCV and CV applicants will increase by 46.39%, 747.15% and 25.09%, respectively, while the number of BEV applicants will decrease by 99.90%. Therefore, active planning and promotion of HFCVs and consumer education campaigns on HFCVs are very helpful in the HFCV market diffusion.

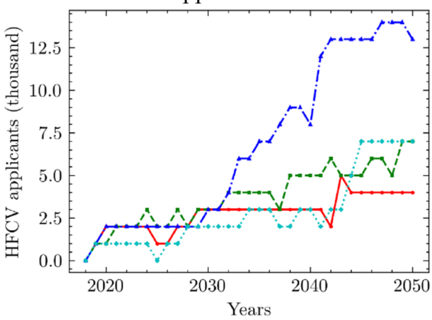
Figure 7 shows that the impact of facility availability perception on the number of applicants for different vehicles from 2018 to 2050. Facility availability perception refers to the extent to which consumers value facility availability when purchasing a vehicle. In this scenario, we test the facility availability perception value from 2.81 to 5.81 with an interval of 1 (parameter β in Eq. (1)) within the four simulation experiments. The higher the value of this parameter, the more consumers care about the refuelling facilities availability when they buy a car. The baseline scenario shows a refuelling facility availability perception coefficient of 4.81, indicating that when consumers purchasing vehicles, they would like to seriously consider facility accessibility. From our analysis, we found that reducing this perception values leads to decreased demand for all vehicle types, particularly affecting PHEVs and CVs. This pronounced effect occurs because the main competitive advantage of PHEVs and CVs are from widespread refuelling infrastructure. Noted that Beijing has consistently classified PHEVs as fuel vehicles, subjecting them to lottery-based licensing and excluding them from some BEV incentives, differing from other regions; additionally, PHEVs on the market have roughly one-third the battery capacity of BEVs and lean more toward CV. Therefore, PHEVs are similar to CVs in Beijing, and thus have similar evolutionary trends. We also found that BEVs are significantly more affected by facility availability perceptions than HFCVs. This may be because BEVs are more popular currently, with users having more direct contact with and reliance on charging facilities, and perceptions of their availability are directly linked to daily usage convenience. In contrast, HFCVs are still in the



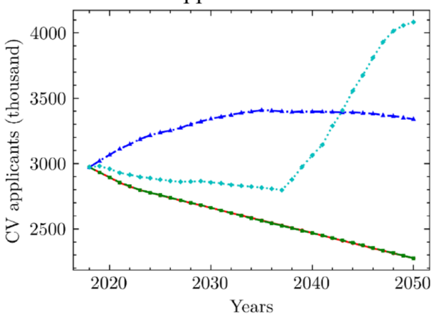
(a) Impact on the Number of BEV applicants



(b) Impact on the Number of PHEV applicants



(c) Impact on the Number of HFCV applicants



(d) Impact on the Number of CV applicants

Fig. 7 The vehicle market applicants expansion under different facility availability (the value is 4.81 in the baseline scenario) promotion stage, and users' perceptions of hydrogen refuelling facilities remain more at a potential level, resulting in a relatively weaker impact.

Environmental preference is also one of the important factors influencing vehicle adoption. Figure 8 shows the evolution of the number of vehicle applicants with different environmental preferences from 2018 to 2050. Environmental preference refers to the extent to which consumers are influenced by the environmental friendliness of a vehicle when purchasing it. It should be noted that we employed the vehicle's carbon emission factor as a surrogate for its environmental friendliness, which means this variable yields a negative purchase utility, as illustrated in Eq. (5). The carbon emission factors involved here are the well-to-tank carbon emissions per kilometre of vehicles disclosed in existing studies (Shin et al. 2019; Wang et al. 2020; Onat et al. 2015). In this scenario, we test the environmental preference value from 2.54 to 5.54 with an interval of 1 (parameter δ in Eq. (1)) within four simulation experiments. It can be found that environmental preference only works at the highest 5.54 for HFCV adoption, has a negative effect on BEVs and CVs, an increase and decrease for PHEVs. In the case of HFCVs, this means that zero-emission HFCVs are more likely to be adopted only when consumers are extremely environmentally conscious (like 4.54). For BEVs and CVs, under the adoption threshold constraint, the more importance potential consumers place on environmental friendliness, the more difficult it is for their adoption intention to exceed adoption threshold, and the less likely they are to purchase them.

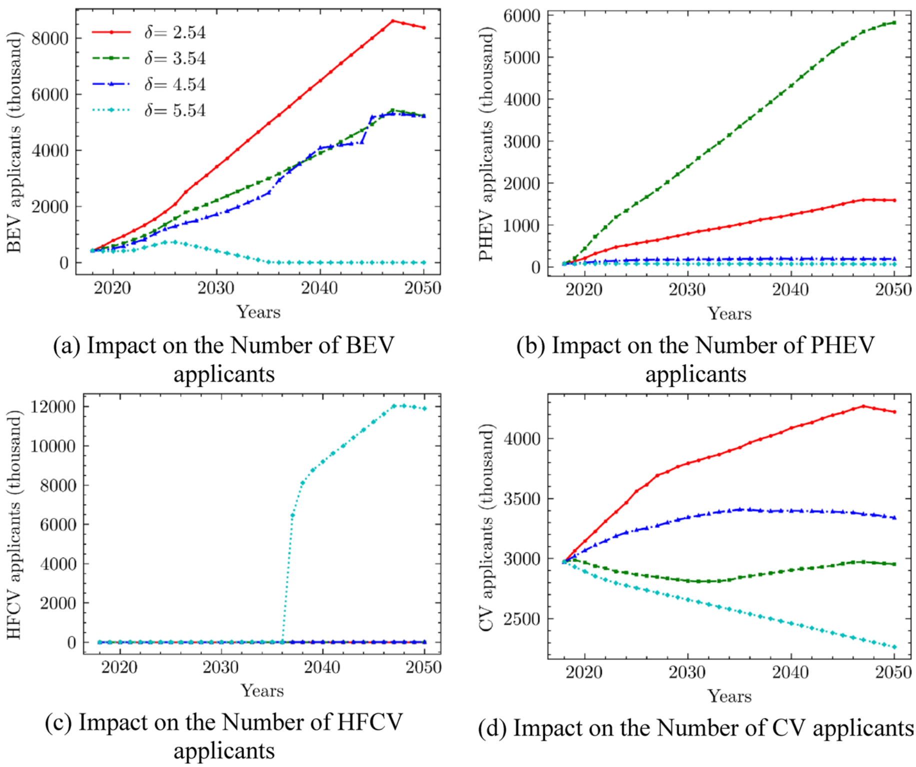
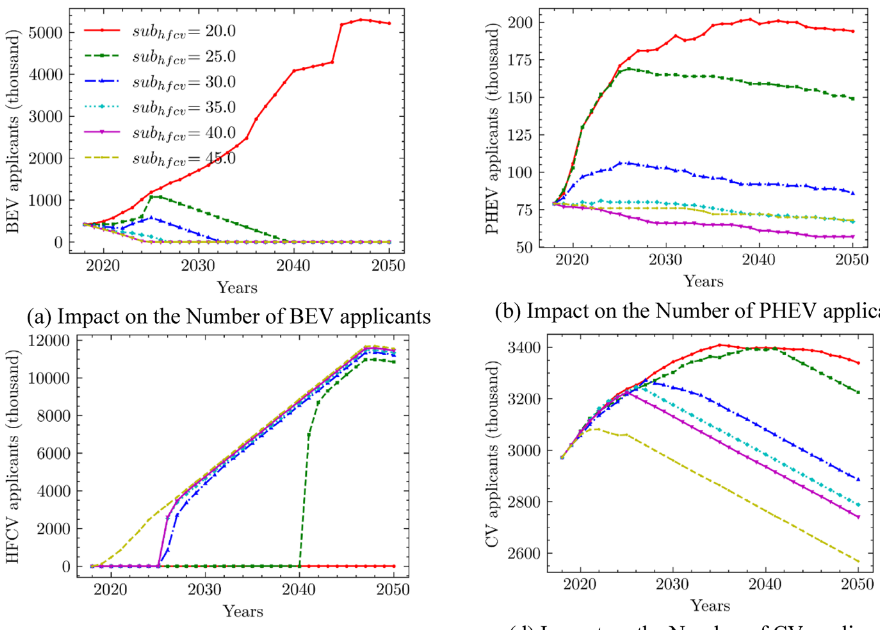


Fig. 8 The vehicle market applicants expansion under different environmental preferences (the baseline scenario value is 4.54)

Impacts of HFCV purchase subsidy

The current high cost of HFCVs has become the most significant obstacle hindering their HFCVs adoption, while purchase subsidies can effectively alleviate this problem and help HFCVs overcome the market diffusion dilemma. In this scenario, we test the HFCV purchase subsidies from 20 to 45 with an interval of 5 (parameter sub_j in Eq. (2) when $j = PHEV$) for a total of six simulation experiments, and the unit here is ten thousand RMB. Figure 9 represents the evolution of the number of applicants in the four vehicles from 2018 to 2050 at different subsidy levels. As expected, the number of HFCV applicants increases with the amount of subsidy and that the HFCV market starts to spread only when the subsidy reaches 25. This also reaffirms that the most critical barrier to the development of HFCVs is the high sales cost. If the subsidy for HFCVs can be increased to 30, the HFCV market will start to see applicants from 2025 onwards. If the subsidy is 25, this HFCV start to appear will be delayed until 2040. This shows that importance of the subsidy, and it means that the psychological price of an acceptable HFCV is around 33 or so. However, we also observed that the HFCV subsidy has a very negative impact on BEVs, and if the subsidy is 25, then BEV applicants will disappear by 2040. This is because BEVs and PHEVs are both clean vehicles with significant complementary substitutes, and this effect should not be ignored. For petrol vehicles, the HFCV subsidy has a negative impact, especially on CV applicants. When the subsidy is increased from 20 to 30, the CV of large-base applicant holdings will also fall by 13.59% by 2050.



(a) Impact on the Number of BEV applicants

(b) Impact on the Number of PHEV applicants

(c) Impact on the Number of HFCV applicants

(d) Impact on the Number of CV applicants

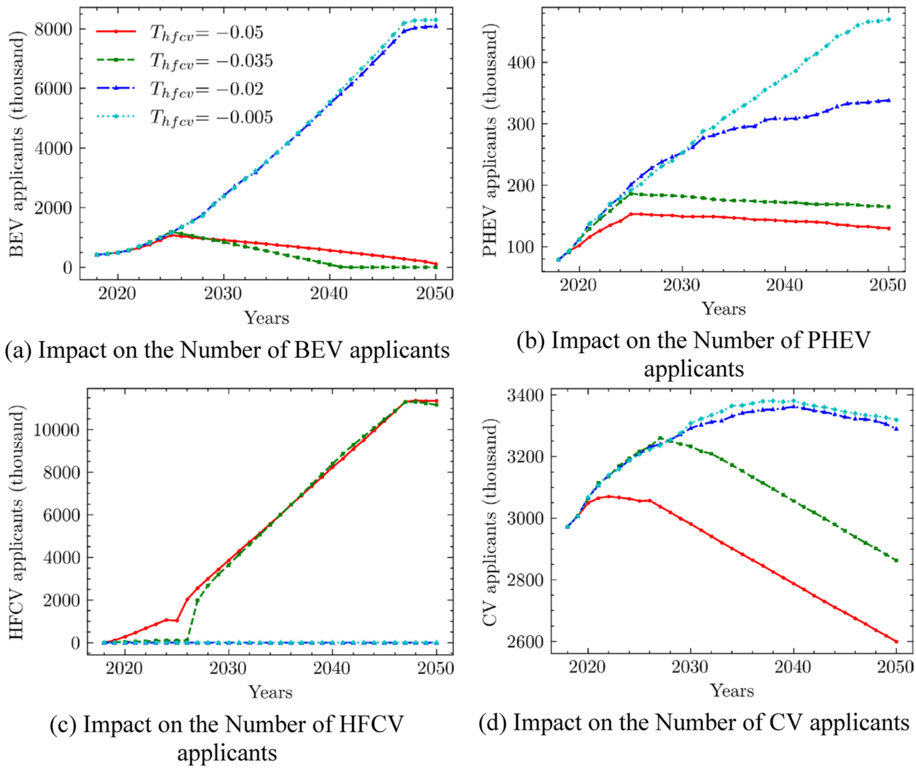
Fig. 9 The vehicle market applicants expansion under different HFCV purchase subsidies (the baseline scenario value is 20)

Impacts of HFCV adoption threshold

The HFCV adoption threshold is a key determinant of consumer conversion from HFCV applicant to vehicle owner. In this scenario, we set up the HFCV adoption threshold as a list ranging from − 0.04 to 0.005 at intervals of 0.015 (parameter T_{hfcv} in Eq. (7)) for a total of four simulation experiments, as shown in Fig. 10. As anticipated, the adoption threshold for HFCVs is negatively correlated with the number of applicants. In contrast, BEVs, PHEVs, and CVs exhibit a positive correlation. This is because as the HFCV adoption threshold increases, more and more people are discouraged from purchasing HFCVs, and this group is moving to other vehicles, including BEVs, PHEVs and CVs. It is also noted that when the HFCV adoption threshold is −0.035, HFCV applicants will begin to appear in the vehicle market in 2026. This threshold is more realistic and should be realized by the adoption strategy. Therefore, lowering the HFCV adoption threshold is one of the key factors in promoting the HFCV market, and consumer education in the HFCV market to reduce their psychological threshold for purchasing HFCVs may be an effective means.

Impacts of HFCV technological learning rates

The HFCV technological learning rate specifies the downward trend of HFCV costs with increasing vehicle production volume. In this scenario, we set up the HFCV technological



(a) Impact on the Number of BEV applicants

(b) Impact on the Number of PHEV applicants

(c) Impact on the Number of HFCV applicants

(d) Impact on the Number of CV applicants

Fig. 10 The vehicle market applicants expansion under different HFCV adoption thresholds

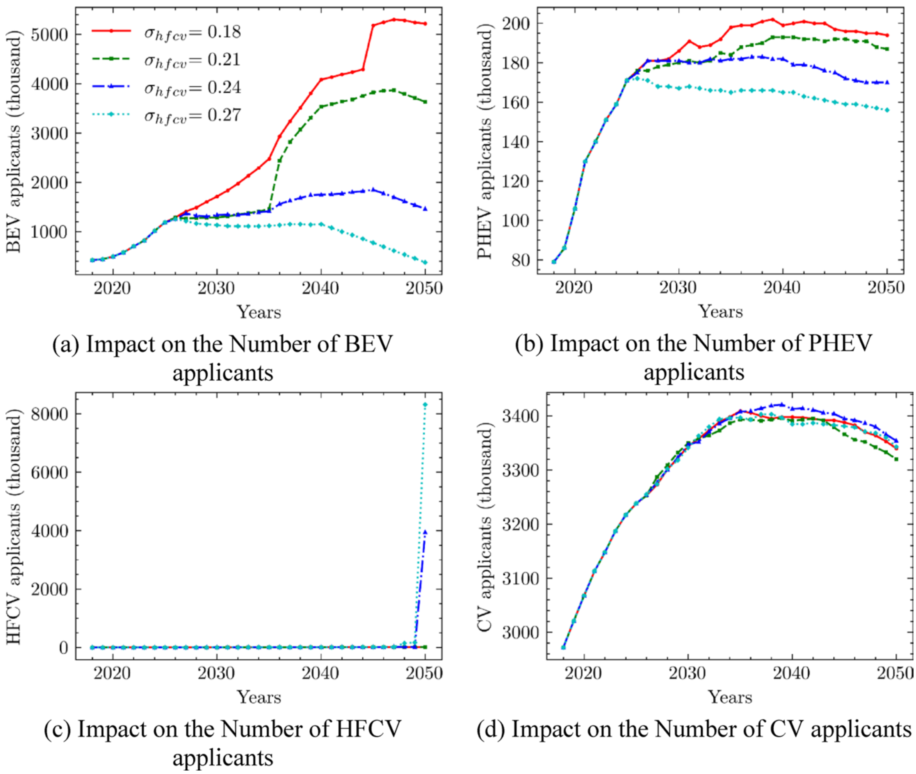


Fig. 11 The vehicle market applicants expansion under different HFCV technological learning rates (the value is 0.18 in the baseline scenario)

learning rate value to a list ranging from −0.04 to 0.005 at intervals of 0.015 (parameter σ_j in Eq. (7) when $j = PHEV$) for a total of four simulation experiments. Figure 11 illustrates the evolution of the number of applicants in the four models from 2018 to 2050 at different HFCV learning rates. We found that the HFCV technological learning rate has no effect on HFCV diffusion. This finding may be unexpected because the preceding HFCV purchase subsidy significantly increased the number of HFCV applicants (see Fig. 9c), while the technological learning rate that reduced HFCV costs did not work in the early stage of simulation. This is because the subsidy for HFCVs is set at a relatively large amount, which greatly reduces the cost of using HFCVs, while the impact of the technology learning rate on the cost is closely related to its cumulative production, and the lower market diffusion rate of HFCVs results in a very limited decline in the cost of HFCVs, which is still very expensive and difficult for consumers to purchase. In addition, the factor has a negative effect on BEVs and PHEVs. For example, when the technological learning rate increases from 0.18 to 0.27, in 2050, there will be a 92.76% and 19.59% decrease in BEV and PHEV applicants, respectively. This finding is also intuitive, as the lower cost of HFCVs leads to a weakening of the cost advantages of BEVs and PHEVs and a decline in the number of applicants. As for CVs, no clear pattern exists, suggesting that the HFCV technological learning rate has a negligible impact on the CV market.

Discussion

Theoretical contributions

Our study contributes to the existing knowledge by developing a bottom-up spatial ABM to simulate the evolution of the HFCV market, incorporating both market competition from other vehicle types and the comprehensive supply–demand market dynamics. Comprehensive market supply–demand dynamics are becoming a cutting-edge modeling mechanism in complex network systems (Huang et al. 2022b; Calderón and Miller 2022). Using this concept, we can more accurately capture the impact of facility market changes on the evolution of the HFCV market and its competitors. Using this model, we have also uncovered some valuable conclusions. For example, HFCVs face significant challenges in overcoming market lock-in by older technologies, which limits the market impact of HSs. Additionally, the successful diffusion of HFCVs is highly likely to negatively affect the BEV market. To the best of our knowledge, our study is the first to employ complex systems theory to reveal the diffusion patterns of HFCVs and identify effective intervention policies from the perspective of comprehensive spatial market supply–demand dynamics.

Practical implications

Our findings highlight that reducing the high sale price of HFCVs is the most critical factor in promoting their adoption. Direct purchase subsidies have been found particularly effective in accelerating market diffusion, as they significantly lower the cost barrier for consumers (Huang et al. 2022a; Liu et al. 2025c). Compared to technological advancements that reduce costs gradually through a learning rate effect, subsidies yield more immediate and substantial results, especially in the early stages of market development. This is consistent with findings in other studies that emphasize the importance of financial incentives in fostering the adoption of sustainable technologies (Khan et al. 2021). Thus, policymakers should prioritize financial support mechanisms over relying solely on long-term technological improvements.

In addition to cost reduction, consumer education campaigns that emphasize the environmental and social benefits of HFCVs are essential. Our results show that increasing social influence perception can lead to a rapid shift in consumer preferences toward HFCVs, even reducing interest in competing technologies like BEVs. This highlights the importance of actively promoting the unique advantages of HFCVs, such as zero emissions and long-range capabilities, while leveraging the relatively limited negative media coverage surrounding them to build a strong, positive reputation. Although the impact of HSs is currently limited, it is more likely constrained by the small size of the HFCV market. Actually, a well-planned infrastructure rollout that aligns with market expansion can instill confidence in potential consumers and address a key barrier to adoption (Huang et al. 2022a). Therefore, policymakers should also prioritize improving the availability of hydrogen refueling infrastructure, as perceptions of facility accessibility will become increasingly significant as the HFCV market grows.

Finally, a balanced approach is necessary to avoid unintended consequences on competing technologies like BEVs. As a leading clean energy vehicle technology, BEVs not only share the advantages of HFCVs but also exhibit immense market potential for integration with power grids and energy systems, highlighting their significant value for large-scale adoption (Liu et al. 2024). Harmonizing the development of both technologies is crucial for achieving a sustainable transition to zero-emission transportation. Currently, BEVs dominate the clean vehicle market; therefore, while promoting HFCVs, policymakers must adopt strategies that ensure complementary development, avoiding excessive constraints on the market space and growth potential of BEVs. For example, attention can be given to differentiated applications by promoting HFCVs in long-distance transportation and heavy-duty sectors while prioritizing BEVs in urban mobility.

Conclusions and policy implications

Although BEVs are the mainstream of transportation electrification vehicles and dominate the majority of the market, as the hydrogen economy develops, the market potential of HFCVs is becoming increasingly important and should not be overlooked. However, existing studies are still limited in modelling the market evolution of HFCVs in the passenger transport sector, especially incorporating both market competition from other vehicle types and the comprehensive supply–demand market dynamics. In response, our study proposed a bottom-up spatial ABM to simulate the evolution of the HFCV market, with the aim of finding effective strategies and policy implications for breaking the diffusion dilemma of the HFCV market.

The key findings are as follows: Under the Baseline Scenario, HFCVs exhibit the fastest annual growth in license applications (37.5%), followed by BEVs (35.52%), PHEVs (4.55%), and CVs (1.72%). However, HFCVs face significant barriers to market penetration, including low ownership, high sales prices, and limited HS availability. Despite a market share growth of 15.63%, HFCVs still rank lowest in both applicants and market share. Additionally, vehicle sale prices show a downward trend, with HFCVs being the most expensive, followed by BEVs, PHEVs, and CVs. Under the What-IF Scenarios, we found that consumer perceptions of cost, social, and environmental factors outweigh facility availability in influencing HFCV adoption. Subsidies for HFCV purchases are more impactful than technological learning rates, significantly accelerating market entry. HFCVs' diffusion strongly affects BEV market diffusion.

Our study provides key policy and managerial insights to promote the diffusion of HFCVs. Policies should prioritize reducing the selling price of HFCVs, improving their reputation, and educating consumers on environmentally responsible behaviour, as these are more critical than the development of HSs. Direct purchase subsidies are particularly effective in accelerating HFCV adoption and market entry, making them a more impactful strategy than technological improvements in vehicle production. In addition, policymakers must balance the promotion of HFCVs with its potential impact on the market space of other technologies, such as BEVs, to ensure a harmonious transition toward sustainable transportation.

While our study offers significant insights, it is essential to recognize its limitations. First, our model applies to cities with license plate policies, such as Beijing and Tianjin, but is not fully applicable to cities without a license plate policy. Future research could extend the generality of the model. Second, our study analyses the HFCV market in a static urban environment, whereas dynamic urban populations may have different HFCV market evolution patterns. Therefore, future studies could consider the evolution of population dynamics to simulate the diffusion of the HFCV market more closely.

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Author contributions X.H. and Z.L. wrote the main manuscript text. S.Z. and J.L. prepared figures and charts. All authors reviewed the manuscript.

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Data availability No datasets were generated or analysed during the current study.

Declarations

Competing interests The authors declare no competing interests.

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