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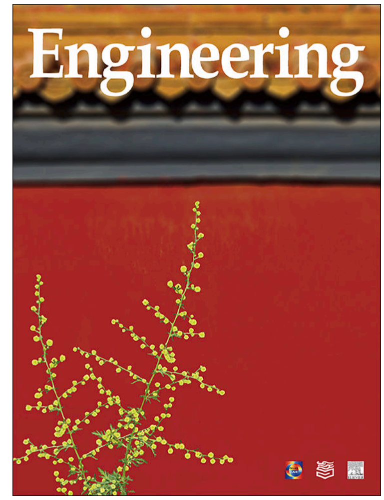

Article

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Exploring Electric Vehicle Purchases and Residential Choices in a Two-Dimensional Monocentric City: An Agent-Based Microeconomic Model

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ABSTRACT

Vehicle electrification, an important method for reducing carbon emissions from road transport, has been promoted globally. In this study, we analyze how individuals adapt to this transition in transportation and its subsequent impact on urban structure. Considering the varying travel costs associated with electric and fuel vehicles, we analyze the dynamic choices of households concerning house locations and vehicle types in a two-dimensional monocentric city. A spatial equilibrium is developed to model the interactions between urban density, vehicle age and vehicle type. An agent-based microeconomic residential choice model dynamically coupled with a house rent market is developed to analyze household choices of home locations and vehicle energy types, considering vehicle ages and competition for public charging piles. Key findings from our proposed models show that the proportion of electric vehicles (EVs) peaks at over 50% by the end of the first scrappage period, accompanied by more than a 40% increase in commuting distance and time compared to the scenario with only fuel vehicles. Simulation experiments on a theoretical grid indicate that heterogeneity-induced residential segregation can lead to urban sprawl and congestion. Furthermore, households with EVs tend to be located farther from the city center, and an increase in EV ownership contributes to urban expansion. Our study provides insights into how individuals adapt to EV transitions and the resulting impacts on home locations and land use changes. It offers a novel perspective on the dynamic interactions between EV adoption and urban development.

1. Introduction

Traffic emissions have long been identified as a critical issue in urban transportation and are among the primary contributors to CO_2 emissions [1,2]. According to the International Energy Agency (IEA), road transport alone is responsible for approximately one-sixth of worldwide total CO_2 emissions, highlighting the urgency for deep decarbonization in this area [3–5]. Due to the increasingly low-emission electricity sources, electric vehicles (EVs) are becoming an important strategy for the decarbonization of road transport [6]. By 2022, EVs represented 14% of all new car sales, totaling over ten million vehicles per year, which contributed to significant environmental milestones with an estimated 80 million tons of greenhouse gas emissions reduction by 2022. Moreover, it is predicted that 18% of new cars sold in 2023 will be electric, suggesting a cont

The transition to electric mobility represents a transformative shift in transportation and urban land use, with far-reaching implications for households, cities, and infrastructure. As EVs become increasingly prevalent, it is essential to understand the factors influencing their adoption and the subsequent impact on residential location choices. Typically, EVs have a higher initial purchase price compared to fuel vehicles (FVs). For example, in January 2024, the average price for new EVs in the United States was 55 353 USD, while it stood at 47 401 USD for FVs, showing a notable difference of 7 952 USD [11]. However, when evaluating operational costs, the scenario shifts significantly. Electricity, as a fuel source, proves to be more cost-effective than conventional fossil fuels. As reported by the IEA [12], in 2022, fuel-economy battery EVs in the United States generally consumed less than 25 kW·h per 100 kilometers, with an average electricity price of 0.15 USD·(kW·h)$^{-1}$ for private charging and 0.30 USD·(kW·h)$^{-1}$ for public charging. In contrast, fuel-economy internal combustion engine vehicles consumed between 5.9 and 10.1 liters of gasoline per 100 kilometers, with an average gasoline price of 1.0 USD·L^{-1} in 2022 [12].

While the operational cost advantages of EVs make them an appealing choice for commuters, the decision to adopt EVs is shaped by a complex interplay of personal, locational, and infrastructural factors. Studies have examined the personal and locational factors influencing the current adoption of EVs from a cross-sectional perspective [13,14]. Duarte et al. [15] assessed the feasibility of wireless charging for EVs in Lisbon, Portugal, as a case study, to address the limited driving range issue in the EV adoption. Rietmann and Lieven [16] conducted an empirical study on the effectiveness of monetary incentive policies in 20 countries. They found tax credits for purchasing EVs are effective but less effective than rebates. Klein et al. [17] use an agent-based simulation to explore how the availability of home charging options affects the diffusion of EVs in Germany. As shown by Klein et al. [17], the importance of home charging options decreases with the improvement of public charging infrastructure. While many researchers have studied the impacts of charging infrastructure on EV adoption [18], limited research focuses on the interactions between public charging infrastructure on EV purchase behaviors and residential location choices.

Despite the growing body of research on EV adoption, there is a notable gap in understanding how these factors interact with residential location choices. The operational cost advantages of EVs make them attractive for commuters, particularly those living far from their workplace. By significantly reducing commuting expenses, EVs have gained popularity as a daily travel option [19]. This is particularly relevant in the context of long-distance commuting trips. The high mileage associated with long commutes amplifies the importance of fuel efficiency and the cost-effectiveness of EVs compared to traditional FVs. Therefore, adopting EVs saves commuters money and allows households to live further from the central business district (CBD) with limited commuting expenses (as shown in Fig. 1). This strategic relocation has the potential to lower house rents without the added burden of higher commuting expenses typically associated with traditional FVs over long distances.

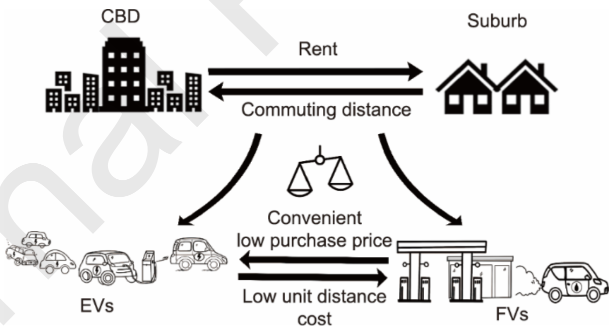

Fig. 1. Trade-off between FVs and EVs.

Furthermore, the interaction between residential relocation and EV adoption has significant implications for urban systems [20], which is consistent with the finding in Ref. [21]. The choice of vehicle energy type is closely linked to commuting patterns [22] and housing decisions, which in turn influence traffic flows [23], urban density, and the spatial distribution of households.

This paper thus aims to analyze how individual households adapt to the transition to electric mobility considering their vehicle type and house location in a monocentric city. Considering that expenses, such as energy consumption and depreciation, are affected by vehicle aging, the impact of heterogeneous vehicle ages is considered. A spatial equilibrium is developed that allows consideration of the interactions between urban density, vehicle age and vehicle type. By dynamically integrating an agent-based model (ABM) framework, we perform micro-simulations of household location preferences and vehicle choices considering a two-dimensional (2D) monocentric urban landscape.

The contributions of this study are twofold. Firstly, it integrates household commuting costs across various vehicle types and residential choices, and analyzes the spatial interactions between them. While extensive research exists on EV adoption [18,24], studies exploring the impact of EV adoption on urban structure are rare. We find that households opting for EVs tend to reside further from city centers, and the increase in EV ownership contributed to urban expansion. Secondly, we investigate the impact of vehicle age on the adoption of EVs and urban structures. To our knowledge, there is limited research on how the age of vehicles affects household locations, although some studies have examined the impact of vehicle age on ownership costs [24]. By analyzing vehicle age distributions over the medium and long term, it is demonstrated that households with old vehi[illegible] way. Moreover, residential segregation caused by the heterogeneity in vehicle age can lead to urban sprawl and congestion.

The remainder of this paper is organized as follows. Section 2 presents the literature review. Section 3 presents a theoretical model to describe household behavior. Section 4 presents the parameter calibration and simulation. Finally, Section 5 discusses the results and concludes the paper.

2. Literature review

2.1. EV purchase behavior

The external factors influencing the decision to purchase an EV can be grouped into three domains: financial, technological, and contextual.

Firstly, financial factors refer to the monetary cost of vehicle purchase and ownership. The comparison of ownership and driving costs between EVs and FVs is considered an important factor influencing consumers' purchasing attitudes and intentions [25]. The EV purchase price has been identified as the most significant obstacle to widespread EV diffusion [26,27]. Cano et al. [26] found that without government incentives, none of the available EVs with a premium satisfied the requirements of over 50% of US consumers. However, EVs offer an advantage over FVs in terms of their operational costs. Electricity is more economical than conventional fossil fuels [28,29]. Dumortier et al. [30] discovered that the financial benefits of reduced energy consumption offset significant or all of the initial price premium in the long term. Therefore, despite the higher initial purchase cost, EVs tend to be more cost-effective because of the lower operating [31–33] and maintenance expenses over their operational lifetime [34].

Secondly, technological factors such as driving range and charging duration are also critical. The limited driving range is frequently reported as a key technical barrier preventing consumers from purchasing EVs [35–38], particularly in regions such as the United States, where reliance on public transit is low, and travel distances can be extensive [39]. In addition, the charging duration of EV batteries is another significant factor that influences consumer adoption. The duration of EV battery charging, which is considerably longer than that of refueling a conventional vehicle [9,40], presents a challenge to the convenience and practicality of EVs for daily use [41]. Other performance characteristics, such as model variety, top speed, and acceleration while contributing to driving satisfaction, are typically considered secondary to cost factors, especially for consumers using EVs for commuting [42,43].

Thirdly, the contextual factor refers to the availability of charging stations, which is another critical determinant in EV adoption. Research has shown that the development of charging infrastructure has a positive impact on saving the searching costs for EV users, thus relieving their range anxiety [44–47]. This is particularly true in dense urban areas where access to home charging is limited [12], making public charging infrastructure a crucial factor for EV adoption. Although early EV adopters are more likely to have the capability to install home chargers, it may lead to the overloading of the electricity distribution system. Tarei et al. [48] highlighted the global issues of electricity distribution system overloading and insufficient charging infrastructure capacity during peak hours, suggesting that inadequate charging reliability and quality can hinder EV adoption. Moreover, the uncertainty in electricity supply plays an important role in charging EVs [49]. Charging control strategies and home energy systems are necessary to reduce peak loads and balance the power grid for home chargers [49–52].

2.2. Interaction between urban land use and transportation

In the field of urban land use–transport interaction (LUTI), extensive research has been devoted to understanding and predicting households' choices regarding residential and job locations, along with the associated daily activity-travel patterns.

The fundamental principle for co-determining land use and transport has been acknowledged by many scholars [53,54], and is supported by theoretical research and empirical findings from different contexts [55–57]. Classical microeconomics theory [58–61] provides a robust framework for qualitative analysis of the long-term relationship between land use and transportation. The development of utility-based models facilitates the capture of complex choice behavior dynamics involved in land use and transport decisions at the individual level [62–64]. In the monocentric city model introduced by Alonso [58], Muth [65], and Mills [66], the city center contained the CBD, which represented access to jobs. Residents made locational choices to maximize their utility by balancing the trade-off between commuting costs and housing affordability. The model predicted decreasing population density, land value, and housing prices as people moved farther from the CBD.

Similar to many purely theoretical studies, these theories employ mathematical formulae for micro-level and individual analyzes. Although the complexities of these models vary, they all share the attributes of conciseness and tractability. However, they encounter challenges in effectively addressing the intricate dynamics between residents and their constructed surroundings, particularly when modeling 2D urban landscapes. Wegener [67] conceived the complex two-way dynamic link between the land-use and transportation systems as a "feedback cycle." Within this cycle, complex interactions exist between several physical, sociodemographic, economic, and policy change forces. Thus, isolating and measuring the mechanisms through which the systems impact each other is challenging.

Grounded in complexity theory, which positions cities as dynamic, adaptive systems comprising multiple interacting components [68], ABMs are increasingly being recognized as a suitable approach for capturing the dynamics of land use and transportation systems. They follow a bottom-up approach that forecasts aggregate urban attributes and land-use patterns emerging at the macro level by simulating the behavior and spatial interactions of individuals at the micro level. ABM can over[illegible]neity among agents, and out-of-equilibrium dynamics and interactions. This provides modelers considerably greater freedom in model design [69–74]. Moreover, ABMs are highly skilled at capturing the dynamic complexities of spatial interactions and effectively represent citywide attributes and land use patterns [75].

As mentioned above, the rising adoption of EVs is beginning to influence household choices of residential locations, potentially reshaping urban land-use patterns. However, the research on the iterations between household location choices and vehicle energy types is rare. As EVs become more prevalent, the relationship between land use and transportation is likely to undergo significant changes, necessitating a deeper exploration of how shifts in vehicle energy types integrate into the broader urban context. To address this, we develop an ABM in this study to simulate the interaction between household residential choices and vehicle energy types, incorporating factors such as vehicle age and the availability of charging infrastructure.

3. The analytical spatial equilibrium model

Consider a monocentric closed city with a CBD located at the center at the crossing of two perpendicular main roads. Thus, the population size N is fixed and all residents work in the CBD. The city is designed as a square with an exogenous maximum boundary. The space is divided into discrete land parcels of unitary size, and each is identified by coordinates (x, y), where x and y represent the horizontal and vertical coordinates, respectively. These parcels are designated solely for residential or agricultural use, and mixed use is prohibited. We measure the distance between the parcels using Euclidean distance. In addition, residents could migrate annually without incurring moving costs.

In this city, each household comprises a single worker and is identical in terms of the daily total available time T, and wage rate w. Households allocate their time to commuting, working, and leisure activities. The wage income for each household is calculated as the product of the wage rate and total working hours. Households encounter a maximization problem wherein they decide on the consumption of a composite good, the amount of housing space, and the amount of leisure time in their parcel (x, y). All parcels are accessible and have an exogenous road capacity F, and the parcels in main road capacity are doubled. Households commuted to the CBD on the shortest path by car. The travel time per unit distance is equal to the sum of the free-flow travel time and congestion delay caused by the aggregate traffic flow. We consider a five-year vehicle scrapping period to capture the perspective of typical households that are used as payback periods for private car owners [76].

3.1. Behavior of households

Following that in literature (e.g., Tikoudis et al. [77], Larson and Zhao [78], and Candia and Verhoef [79]), a constant elasticity of substitution (CES) utility function U is adopted to model the utility of households at a given residential location (x, y), which is given by

$$U = [(\delta_s s(x,y))^{\rho} + (\delta_z z(x,y))^{\rho} + (\delta_l l(x,y))^{\rho}]^{1/\rho} \quad (1)$$

where δ_s, δ_z, δ_l, and $\rho \leq 1, \rho \neq 0$ are exogenous parameters and $\sigma = 1/(1-\rho)$ represents the elasticity of substitution in the CES function between housing $s(x,y)$, non-spatial composite goods $z(x,y)$, and leisure time $l(x,y)$. Households have a total time endowment T, which is used for working $t_w(x,y)$, commuting $2t_c(x,y)$, and for leisure $l(x,y)$. Then, the time budget of households is expressed as:

$$T = t_j(x,y) + 2t_c(x,y) + l(x,y) \quad (2)$$

Thus, households' working time $t_j(x,y)$ is expressed as:

$$t_j(x,y) = T - 2t_c(x,y) - l(x,y) \quad (3)$$

We assume that everyone has the same wage rate w, and that households' wage income depend only on their working time t_w. Denote the households' wage income as I, and we have:

$$I(x,y) = t_j(x,y)w \quad (4)$$

Household consumption includes expenditures on non-spatial composite goods, rent, and commuting. Thus, the total household consumption is expressed as:

$$pz(x,y) + r(x,y)s(x,y) + e_k^n(x,y) = I(x,y), \quad k = \{\mathrm{FV,EV}\}, n = \{1,2...,5\} \quad (5)$$

The market price of the composite good is p, the rent cost per unit of land at location (x, y) is $r(x, y)$, and $e_k^n(x,y)$denotes the commuting cost of type k vehicles of age n. Substituting Eq. (4) into the budget constraints (Eq. 5), the budget constraint is given by:

$pz(x$

It is helpful to define $M(x, y)$ as the maximum income after commuting costs that can be realized when leisure time is chosen to be zero, which is given by Candia and Verhoef [79]:

$$M(x,y) = w(T - 2t_c(x,y)) - e_k^n(x,y) \quad (7)$$

Maximizing Eq. (1) on the parcel (x, y) and subject to Eq. (6) yields the Marshallian demand functions for composite goods, housing space, and leisure time (Eqs. (8)–(10)), which are given by:

$$z^*(x,y) = M(x,y)\frac{(\delta_z{}^{\rho}/p)^{\sigma}}{(\delta_s/r(x,y))^{\chi}+(\delta_l/w)^{\chi}+(\delta_z/p)^{\chi}} \quad (8)$$

$$s^*(x,y) = M(x,y)\frac{(\delta_s{}^{\rho}/r(x,y))^{\sigma}}{(\delta_s/r(x,y))^{\chi}+(\delta_l/w)^{\chi}+(\delta_z/p)^{\chi}} \quad (9)$$

$$l^*(x,y) = M(x,y)\frac{(\delta_l{}^{\rho}/w)^{\sigma}}{(\delta_s/r(x,y))^{\chi}+(\delta_l/w)^{\chi}+(\delta_z/p)^{\chi}} \quad (10)$$

where $\chi = \rho/1-\rho$. Substituting Eqs. (8)–(10) into the utility function in Eq. (1) yields the indirect utility function:

$$V(x,y) = M(x,y)\left((\frac{\delta_s}{r(x,y)})^{\chi} + (\frac{\delta_l}{w})^{\chi} + (\frac{\delta_z}{p})^{\chi}\right)^{1/\chi} \quad (11)$$

3.2. Commuting time and travel cost

All households commute to the CBD via EVs or FVs. Commuting time depends on the traffic speed on the road to the CBD. Based on the "Bureau of Public Roads" specification [78] of the traffic congestion function, the traffic speed function $S(i, j)$, is expressed as

$$S(i,j) = \frac{1}{a+b(Q(i,j))^c} \quad (12)$$

where a, b, and c are traffic congestion parameters, i and j represent the horizontal and vertical coordinates of road segments, respectively, and and $Q(i, j)$ is the ratio of the aggregate traffic flow to the exogenous road capacity $R(i, j)$, which is expressed as:

$$Q(i,j) = \frac{1}{R(i,j)}\sum_{(x,y)\in K} H(x,y)\delta_{(i,j),(x,y)} \quad (13)$$

Here, $H(x,y)$ represents the number of households in the parcel (x,y). Dummy variable $\delta_{(i,j),(x,y)}$ equals 1 if (i, j) is on the path from (x,y) to CBD, and 0 otherwise. Thus, the commuting time at location (x, y) is expressed as:

$$t_c(x,y) = \sum_{(i,j)\in P_{(x,y)}} \frac{d(i,j)}{S(i,j)} \quad (14)$$

where the set $P_{(x,y)} = \{(i,j)|\delta_{(i,j),(x,y)} = 1\}$, $d(i, j)$ represents the traveling distance of the parcel (i, j), which is related to cell resolution and direction.

The commuting travel costs of households include the annual fixed cost of owning a vehicle, O_k, maintenance costs related to the length of commuting trips m_k, and energy consumption costs of commuting trips. The annual fixed cost of a vehicle depends on its purchase price and the annual depreciation rate [76,80]. The fixed cost of owning a car in year n is thus given by:

$$O_k(n) = O_k^1(1 - 0.10)^{n-1} \quad k = \{\text{FV,EV}\}, n = \{1,2...,5\} \quad (15)$$

where O_k^1 is the fixed cost for the first year of owning a k energy-type vehicle. Following Larson and Zhao [78], the fuel consumption per kilometer of the FVs is given by:

$G_{\mathrm{F}}(i,j) = \frac{\alpha_1}{\quad}$ (16)

where the denominator is a fourth-degree polynomial function of velocity, representing fuel efficiency in miles per gallon [81]. Following Fiori et al. [82], the electricity consumption per kilometer of the EVs is given by

$$G_{\mathrm{E}}(i,j) = \beta_1 + \beta_2 S(i,j) + \beta_3 S(i,j)^2 \qquad (17)$$

where $(\alpha_1,\alpha_2,\alpha_3,\alpha_4,\alpha_5,\alpha_6)$ and $(\beta_1,\beta_2,\beta_3)$ are technical parameters [83,84][†].

Considering the challenges associated with the driving range and charging times, we further assume that an extra cost ϑ, is required for households with EVs. Moreover, we assume that households do not have home chargers for their EVs, and thus they can only use public charging piles [17][‡].

The driving ranges of EVs depend on the degradation of battery capacity [85,86], and the reduction in the battery capacity requires more frequent charging, which causes inconvenience and range anxiety for the owners. In our study, we assume the battery capacity of EVs decays exponentially at a rate of $(1-\tau)$, where τ represents the annual decay rate of battery capacity. This means that the battery capacity of an EV aged *n* years is $(1-\tau)^{n-1}$ times its original capacity, and define the extra cost $\vartheta(n)$ as

$$\vartheta(n) = A(1-\tau)^{1-n}\mathrm{e}^{\gamma} \qquad (18)$$

where A is a constant that signifies the inconvenience related to technological drawbacks, and γ is the ratio of the number of EVs to the number of public charging piles within a given window $\widehat{W}$, which includes its own and adjacent cells. With τ set at 0.05 in our simulations, the capacity in the fifth year $(n = 5)$ approximately reduces to 81.5% of its initial value, closely aligning with many studies suggesting a retirement capacity near 80% [85,87–89].

Based on the above analysis, the commuting expenses of households with *n*-year-old EVs are thus given by:

$$e_{\mathrm{E}}(x,y,n) = O_{\mathrm{E}}(n) + 2\sum_{(i,j)\in P_{(x,y)}} (m_{\mathrm{E}} + p_{\mathrm{E}} G_{\mathrm{E}}(i,j)) d(i,j) + \vartheta(n) \qquad (19)$$

where p_{E} represents the market prices of electricity. In this study, we assume that key EV parameters, including original battery capacity, purchase prices, and electricity consumption rate, remain fixed throughout the time scale considered. This approach allows us to focus on the EV depreciation costs associated with vehicle aging. However, future analyses should explore the impact of variations in these parameters.

As for FVs, the wear and tear on engine components such as oil pumps, valves, and fuel injectors, can deteriorate over time, leading to less efficient fuel consumption [90,91]. We assume a linear increase in FVs' operational costs, $1 + \varepsilon(n-1)$, to depict the increase in fuel consumption with vehicle aging. Thus the commuting expenses of households with *n*-year-old FVs are given by:

$$e_{\mathrm{F}}(x,y,n) = O_{\mathrm{F}}(n) + 2\sum_{(i,j)\in P_{(x,y)}} (m_{\mathrm{F}} + (1 + \varepsilon(n-1)) p_{\mathrm{F}} G_{\mathrm{F}}(i,j)) d(i,j) \qquad (20)$$

where ε is an age-related ratio for FVs, and p_{F} represents the market prices of fossil fuels. For example, if $\varepsilon = 0.05$, it means that as vehicles approach their end of life, their operational costs will be 20% [92] higher than those of new vehicles.

3.3. Dynamics based on an ABM framework

We assume that at the beginning of the study period, all residents in the city commute via FVs, with the vehicle fleet characterized by a uniform discrete age distribution, meaning that an equal number of vehicles existed for each age group in the city. Residents make house location choices, and an initial equilibrium is achieved in the first year.

As mentioned above, vehicle age affects fixed costs, and operating expenses (and thus commuting costs) increase

[†] The electricity consumption equation, Eq. (17), is derived from a quadratic regression line that was calibrated using the least-squares regression method on real trajectory data. This database originates from the US Department of Transportation, the Federal Highway Administration's Next Generation Simulation (NGSIM) program [83], and the EU project MULTITUDE [84]. The NGSIM data is highly regarded as one of the most valuable sources of microscopic traffic data and has been extensively utilized by researchers globally to further advancements in traffic flow theory. The dataset includes real driving data, simulated data, and standardized test cycle data. The diversity and representativeness of these data enhance the reliability and broad applicability of the equation's predictive outcomes.

[‡] It should be noted that purchasing EVs sometimes come with home chargers, especially for early EV adopters. However, this is not always possible for urban households, particularly in dense urban environments with limited private parking spaces, making public charging infrastructure critical for EV adoption. As shown in Klein et al. [17], the importance of home charging options decreases with the improvement of public charging infrastructure. Therefore, we only consider the case with public charging piles. However, home chargers do affect household behaviours in their residential location choices, which should be explored in the future.

significantly with vehicle age. Moreover, vehicles that reach the end of their lifespan undergo recycling processes over time, and [illegible] rium established in the last year does not hold due to the change in the vehicle age structure. Thus, residents relocate by making location and vehicle type choices, guided by the indirect utility function (defined in Eq. (11)), until a new equilibrium is established.

Each year, the proposed ABM framework employs the concept of a time step t to dynamically simulate residents' behaviors and decisions within an urban environment (as illustrated in Fig. 2). At each time step t, a unit of residents select a location to settle to maximize their indirect utility function, U^t, given in Eq. (11) based on the spatial distribution and rent in the city at $t-1$. We model a sequence of short-term equilibria that prevented the intra-city relocation of households [93,94]. Rents are adapted at every time step to consider alterations in costs and utility. In equilibrium, the rent rate for each residential parcel (x, y) at each time step t is given by:

$$r^t(x,y) = \delta_s\Big(\big(\frac{U^t}{M(x,y)}\big)^{\chi} - \big(\frac{\delta_l}{w}\big)^{\chi} - \big(\frac{\delta_z}{p}\big)^{\chi}\Big)^{-1/\chi} \qquad (21)$$

Herein, land, as a resource carries exogenous opportunity costs. This cost can be equated to the revenue derived from agricultural production. Thus, the city's land rent rate has a minimum value equal to the agricultural land rent, R_{A} [75,79]. If the adapted rent rate $r^t(x,y) < R_{\mathrm{A}}$ because of increased travel costs, households will reconsider their residential selection within the city. An equilibrium is achieved when all households have settled in the city, each achieving a uniform utility level and cannot improve their utility by unilaterally changing their locations or vehicle type.

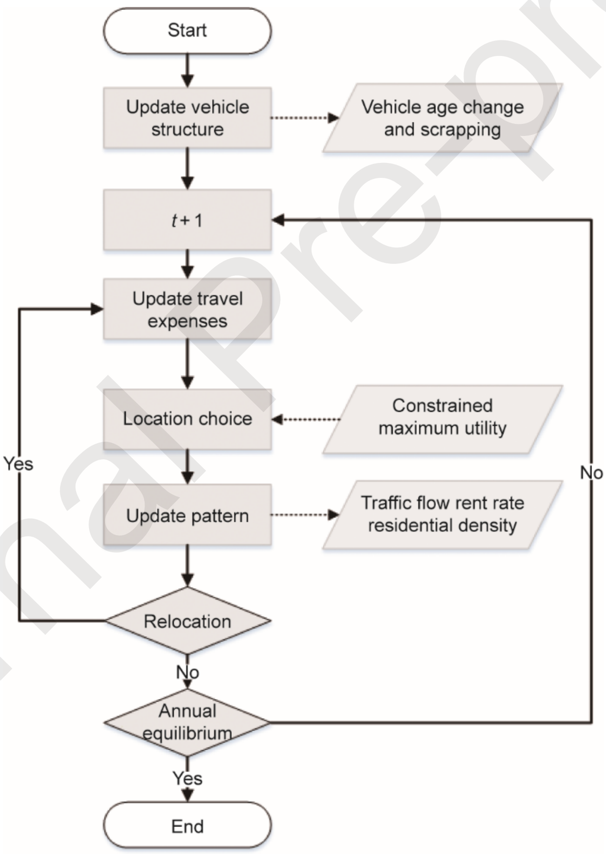

Fig. 2. Annual processes of ABM with heterogeneous agents and the feedback of EV adoption on residential location choice. *t*: time step.

4. Simulations

To illustrate the proposed model, we conduct the following simulations. First, we consider only FVs and analyze the impact of heterogeneity in vehicle age on resident choices and urban structures. We then introduce EVs as alternatives and analyze household preferences for vehicle types. Finally, we explore the factors that affect EV adoption.

4.1. Benchmark scenario

In this section, a simulation is conducted for the benchmark scenario wherein all households used FVs for commuting and the distribution of vehicle ages is uniform ($N_{\mathrm{F},i} = \frac{N}{5}, i = 1, 2,..., 5$). The number of households is set at $N = 100\,000$, with a daily time endowment of $T = 16$ h. Further, the wage rate in the city is $w = 60$ RMB$\cdot$ h^{-1}. The current price of No. 95 gasoline in Beijing is approximately 9 RMB$\cdot$L^{-1}, and thus we set $p_F = 9$. The traffic congestion parameters are $(a, b, c) =$ [illegible], indicating that the free-flow traffic speed equals 40 km$\cdot$h^{-1}, and that the congestion delay and aggregate traffic flow are linearly related. Following Larson and Zhao [78] and Fiori et al. [82], the technical parameters of the energy consumption function (Eqs. (16) and (17)) are set as $\alpha_1 = 3.78/1.6$, $\alpha_2 = 0.822$, $\alpha_3 = 1.83$, $\alpha_4 = -0.0486$, $\alpha_5 = 0.000651$, $\alpha_6 = -0.0000037$, $\beta_1 = 0.143$, $\beta_2 = -0.00191$, and $\beta_3 = 0.0000228$ [78,82]†. Considering the Chinese automobile market, the price of the FVs is set at 150 000 RMB. The agricultural land rent R_A, is fixed at 40 RMB for one unit of space per day, implying a minimum monthly rent of 1200 RMB for a house with one unit of space.

We standardize the weight parameter for composite goods δ_z, to 1 and calibrate other parameters using data from the Beijing Transport Development Annual Report [95]. The calibration results are presented in Table 1, where the commuting distance, time, working hours, and housing costs are expressed on a daily per capita basis. In the benchmark scenario (row 1 of Table 1), the resolution is set to 1 km, $(\delta_s, \delta_l, \delta_z) = (200.93, 27.73, 1.00)$, [79] and $\rho = -1$, resulting in a CES between housing space, leisure time, and composite goods of $\sigma = 1/2$. The simulation parameters result in an average daily commuting distance of 9.02 km, commuting duration of 1.27 h, and working hours of 8.34 h, which closely align with the actual situation in Beijing (China). In this scenario, the monthly average wage in the city is 11 008.8 RMB, including an average monthly housing expenditure of 3 943.06 RMB and a commuting cost of 1 549.76 RMB, with the remainder spend on composite goods.

Table 1
Parameters calibration for the benchmark.

Scenario	Parameter values $(\delta_s, \delta_l, \delta_z, \rho, R_A)$	Resolution (km)	Commuting distance (km)	Commuting time (h)	Working hours (h)	Housing cost (RMB)
Scenario 1	(200.93, 27.73, 1.0, −	1.0	9.02	1.27	8.34	179.23
Scenario 2	(150.93, 47.73, 1.0, −	1.0	7.67	1.13	9.20	197.70
Scenario 3	(150.93, 47.73, 1.0, −	1.5	14.21	1.94	8.90	227.96
Scenario 4	(200.93, 27.73, 1.0, −	2.0	16.04	2.39	7.92	198.25
Scenario 5	(250.93, 17.73, 1.0, −	1.0	6.21	0.98	7.76	150.33
Scenario 6	(200.93, 37.73, 1.0, −	1.0	11.41	1.59	8.66	197.24
Scenario 7	(200.93, 27.73, 1.0, −	1.0	9.97	1.44	8.62	188.02
Scenario 8	(200.93, 27.73, 1.0, −	1.0	10.30	1.32	8.14	182.41

Fig. 3 shows that households with different vehicle ages form a pattern of residential segregation. The city layout extends diagonally, instead of along the main roads, which is related to our assumption that residents take the shortest distance to work. When commuting to the CBD, residents prioritize minimizing the distance over avoiding congestion. This preference result in a dominant trend of approaching the CBD via diagonal routes within adjacent parcels, effectively reducing the length in both the x and y directions. Consequently, residents located on these diagonal paths travel directly to the CBD, whereas those in other areas initially move diagonally towards the main roads before following them to the CBD. The main roads, which serve as a collective route for households from various parcels, become heavily congested. Households avoid this congestion by living near diagonals, even if this implies a longer distance from the CBD. This choice results in a distinctive city outline characterized by expansion outward along the diagonal axes.

† The parameters (α_2–α_6) of the electricity consumption equation, Eq. (17), are derived from a quadratic regression line resulting from fitting a fourth-degree polynomial to empirical data provided by Ref. [78]. The inverse of the fuel efficiency function yields a fuel consumption function in gallons per mile. For convenience in calculations, we use the numerator, α_1, to convert this into the international unit of liters per kilometer. The conversion factor 3.78 is used to convert gallons to liters, and 1.6 is the conversion factor from miles to kilometers. Meanwhile, the parameters (β_1–β_3) refer to the coefficients from the fitting curve for EVs as given by [82].

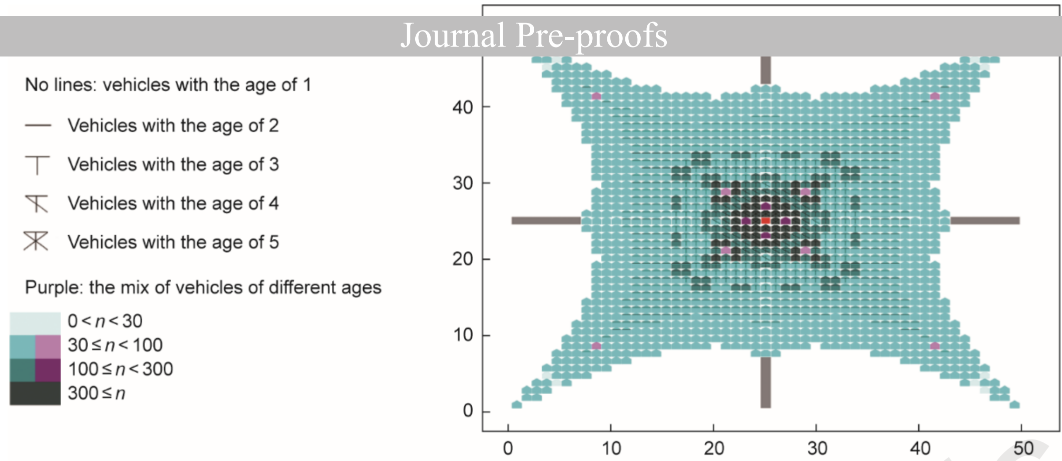

Fig. 3. Urban structures of benchmark: household density (darker color: greater density, CBD: the red square in the center).

As shown in Fig. 3, the heterogeneity in vehicle age leads to residential segregation. Residential circles radiate from the CBD to the periphery of the city based on vehicle age heterogeneity. Vehicle age declines from the CBD towards the boundary, indicating a concentration of households with older vehicles in city centers. In contrast, households with newer vehicles tend to cluster near the boundary of the city, as depicted in Fig. 3. This may be because the commuting expenses of older vehicles are much more sensitive to the travel distance, which makes them choose house locations near the center. In contrast, the commuting expenses of newer vehicles are less sensitive to the travel distance, and the high fixed cost of newer vehicles may limit households to more affordable areas further from the high-rent city center. Given that older vehicles typically exhibit lower efficiency and adhere to lower emission standards, this pattern suggests a potential exacerbation of traffic congestion and emissions in the city center due to the prevalence of older vehicles.

According to the standard monocentric model of spatial structure, population density is expected to decline with increasing distance from the CBD [58,65,66], a phenomenon strongly supported by empirical evidence [96–99]. The same trend is shown in Fig. 3, as residential density generally decreases from the CBD toward the boundary of the city. It suggests a preference among residents to live closer to the city center to minimize commuting distances [100–102]. Within residential zones characterized by the same vehicle age, the residential density consistently diminishes as the distance from the city center increases. It should be noted that the initial density in a residential zone composed of newer vehicles may exceed that at the periphery of a residential zone dominated by older vehicles.

4.2. Equilibrium with EVs

In this section, we introduce EVs as alternatives to household commuting. We assume that a vehicle must be scrapped after five years. Before that, households are provided the opportunity to replace their vehicle with a new one at the start of each year. We set the electricity price of the charging piles as $p_{\mathrm{E}} = 1.5$, the decay rate of battery capacity as $\tau = 0.05$, and the purchase price of EVs to be 160 000 RMB, which is slightly higher than that of FVs. The number of charging piles is 100 per square area, and the number on the vertical main roads is doubled. The constant parameter of inconvenience cost (IC) in Eq. (18) is given by $A = 100/\mathrm{e}$, implying that if there are 100 households with EVs in a square that is not close to the main road, the IC they suffer every day is equivalent to an economic loss of about 40 RMB. The other conditions are similar to the benchmark situation. We conduct simulations in the city for ten years (i.e., two scrapping cycles).

Fig. 4 illustrates the annual trends in the proportion of EVs, electric consumption (kW·h), and fuel consumption (L). EV adoption shows a consistent growth in EV adoption from the first year to the fifth year (i.e., during the first scrapping cycle period). The proportion of EVs reaches its maximum value in the fifth year, which is above 0.5 (i.e., the number of EVs exceeds that of FVs). However, the proportion of EVs has a large decrease in the sixth year. After that, it begins to increase again until the ninth year, and encounters a decrease in the last year. The final proportion of EVs is about 0.34, which is close to that in the fourth year. Over a decade, the proportion of EVs increases significantly, peaking in the fifth year. This shift towards EVs correlates with a rise in electric consumption and a decline in fuel consumption (as shown in Fig. 4(a)). The data shows that as more EVs are adopted, the overall vehicles' energy cost structure transitions from gasoline to electricity, reflecting the changing consumption of energy use in urban transportation.

Fig. 4(b) presents the proportion of households that chose to replace their cars each year. It can be observed that the proportion of households that chose to replace their cars annually (the sum of EVs and FVs) is approximately 0.2, which is close to the proportion of vehicles forced to be scrapped every year. It implies that almost no households actively replaced vehicles with new ones before they reach the scrapping year. Hence, only the original FVs in the city are scrapped annually in the first scrapping period, and car owners reselect vehicle energy types, which explains the growth of EVs in the first scrapping period.

However, in the sixth year, the proportion of EVs decreases significantly, which is related to the housing competition between EV and FV owners. The FVs near the EV distribution area are new cars with a car age of one year. They are distributed in the outermost layer of the area where the central FVs are located. At the beginning of the sixth year, the cars from the first year, mainly EVs reach the end of their five-year lifespan. As a result, these car owners have to choose a new ener ... eing FVs, as shown in Fig. 4(b). Due to the owners of old FVs living in high-density residential areas close to the CBD, the residential structure of the city is compact. Choosing FVs can benefit more from lower purchase prices than EVs. Therefore, households chose FVs more, resulting in a large decrease in EVs in the sixth year. The same reason can also explain the large number of EVs in the fifth year and the large number of FVs in the tenth year.

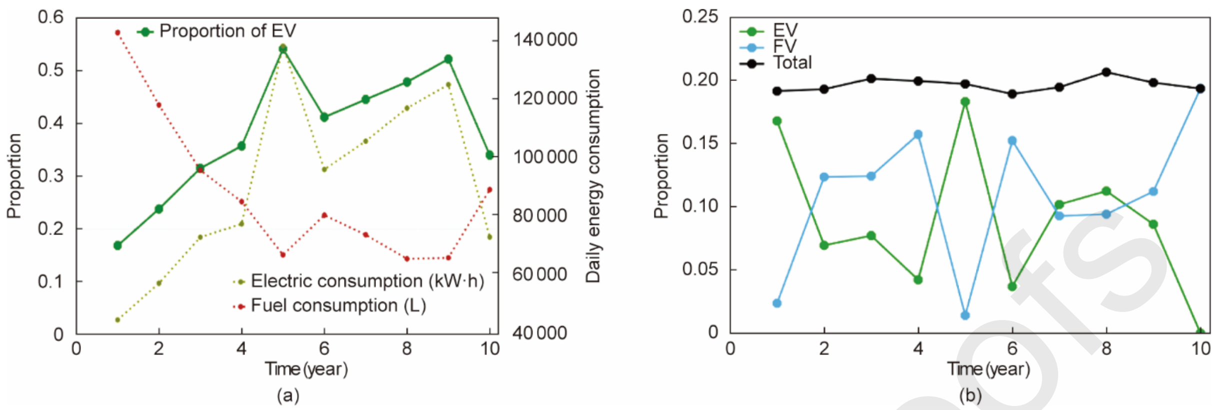

Fig. 4. Temporal evolution of EV adoption and energy cost. (a) Evolution with energy consumption; (b) annual new vehicles.

Fig. 5 is an energy cost contour plot. It consists of two contour plots depicting fuel cost (left) and electricity cost (right) for year ten. They represent varying levels of fuel cost in liters and different levels of electricity cost in kW·h. These plots show the energy consumed by each household if they use a vehicle for commuting in that location. The central area shows the lowest energy costs, with costs increasing outward. The shape of the fuel cost contours indicates a non-uniform distribution, likely influenced by factors such as distance and congestion levels. In contrast, the electricity cost contour plot demonstrates a more uniform and predictable pattern.

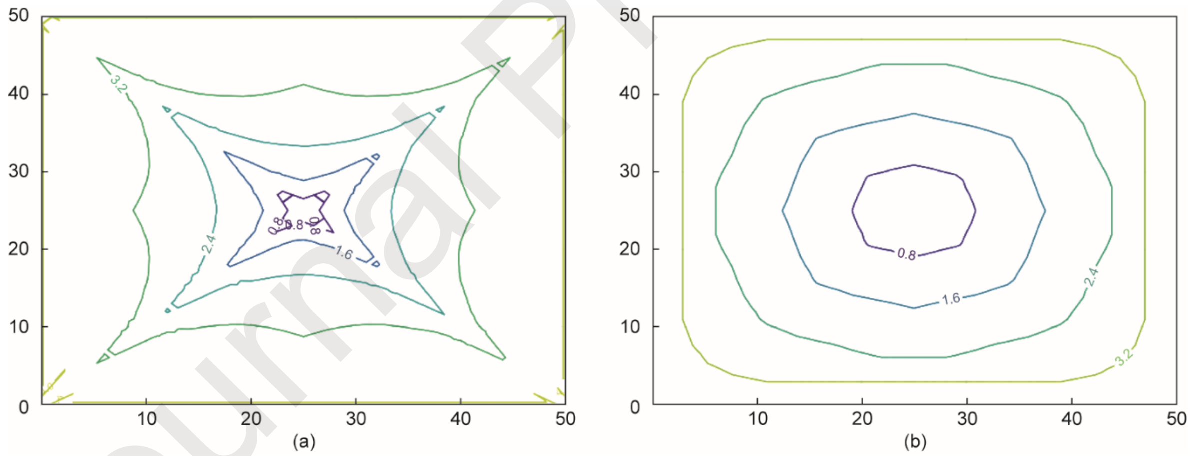

Fig. 5. Energy cost contour plot of year ten: (a) fuel cost (L) and (b) electricity cost (kW·h).

According to the latest internal combustion engine fuel economy data released by the IEA, each gallon of gasoline produces approximately 8887 g of CO_2. Based on this, each liter of gasoline generates about 2350 g of CO_2. Electricity emissions vary depending on the source of the electricity and can be categorized into low-carbon and high-carbon scenarios. In the low-carbon electricity scenario, where the primary sources are renewable energy or nuclear energy, 1 kW·h of electricity consumed produces 50 g of CO_2. Conversely, in the high-carbon electricity scenario, where the primary sources are coal or natural gas, 1 kW·h of electricity consumed produces 800 g of CO_2. In practice, the emission intensity of electricity generation varies by country and region, reflecting a mix of these scenarios. For instance, in 2020, China's emission intensity is approximately 600 g of CO_2 per 1 kW·h, representing a blend of low-carbon and high-carbon energy sources [103,104]. Based on these data, we plot the overall trend in carbon emissions as shown below.

Fig. 6 illustrates the change in CO_2 emissions relative to the proportion of EVs. The red line represents CO_2 emissions from fuel consumption, which shows an inverse trend to the proportion of EVs. Notably, even in the fifth year, when the proportion of EVs is at its peak, CO_2 emissions from fuel consumption remain twice as high as those from electricity consumption (yellow line), and they consistently constitute a significant portion of the overall CO_2 emissions (black line). CO_2 emissions from electricity consumption exhibit the same trend as the proportion of EVs, primarily due to the reliance on high-carbon electricity sources. This indicates that despite the growth in EV adoption, there is substantial potential for further carbon reduction by transitioning to cleaner energy sources.

C [...] able 2 shows the direct correlation between increased commuting time and reduced leisure and working hours, which adversely affect individual well-being and the economy. Moreover, there is a notable positive relationship between the number of land squares developed for housing, commuting distance, and commuting time. In the fifth year, the city reaches its maximum spatial scale with 2292 housing squares, resulting in the highest average commuting distance (13.54 km) and time (1.95 h), both of which exceed the figures in the baseline scenario. However, the tenth year stood out as an exception. Its average commuting distance decrease to 8.78 km, in contrast to the benchmark of 9.02 km. However, commuting time has increased, which is linked to the distribution of residences. Compared with the benchmark, areas near the CBD exhibit a higher presence of low-density squares. These are encircled by high-density enclosures, leading to increased congestion [105].

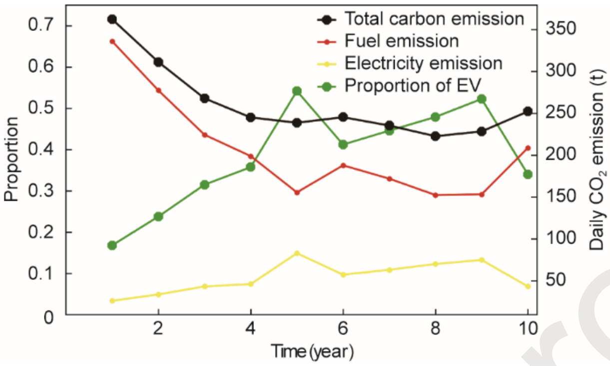

Fig. 6. Annual trends of EV proportion and CO_2 emissions.

Table 2
Output of annual equilibrium with EVs.

Year	Developed square	Proportion of EVs	Commuting time (h)	Leisure time (h)	Commuting distance (km)	Housing cost (RMB)	Working hours (h)
1	1471	0.17	1.27	5.17	9.04	173.96	8.30
2	1475	0.24	1.26	5.15	8.83	175.64	8.32
3	1582	0.31	1.30	5.09	9.21	177.12	8.30
4	1531	0.36	1.30	5.11	9.22	173.99	8.27
5	2292	0.54	1.95	4.07	13.54	194.52	8.02
6	1761	0.41	1.47	4.85	10.49	178.92	8.21
7	1887	0.45	1.54	4.72	11.07	183.32	8.21
8	2034	0.48	1.61	4.58	11.79	187.99	8.21
9	2104	0.52	1.76	4.41	12.50	185.07	8.08
10	1471	0.34	1.32	5.13	8.78	170.12	8.22

Fig. 7 illustrates annual overall average trends in various variables within our model over 11 years. These variables include commuting time, commuting distance, housing space, rent, leisure time, non-spatial composite goods cost, and working time. In Figs. 7(a)–(e), the left y-axis shows average commuting time, while the right y-axis represents different variables. Fig. 7(f) presents the changes in working time and leisure time. Fig. 7(a) depicts the trends in commuting time (gray line) and commuting distance (cyan line). Both metrics show minor fluctuations from the baseline year (year 0) to year 4. However, in year 5, there is a noticeable increase, with commuting time rising from 1.3 h in year 4 to over 1.9 h. Similarly, the commuting distance increases by more than 4 km, exceeding 13 km. This pattern mirrors the trend observed in the proportion of EVs, where both metrics sharply decline in year 6, followed by growth that continues until year 9. In the final year, both commuting time and distance decrease.

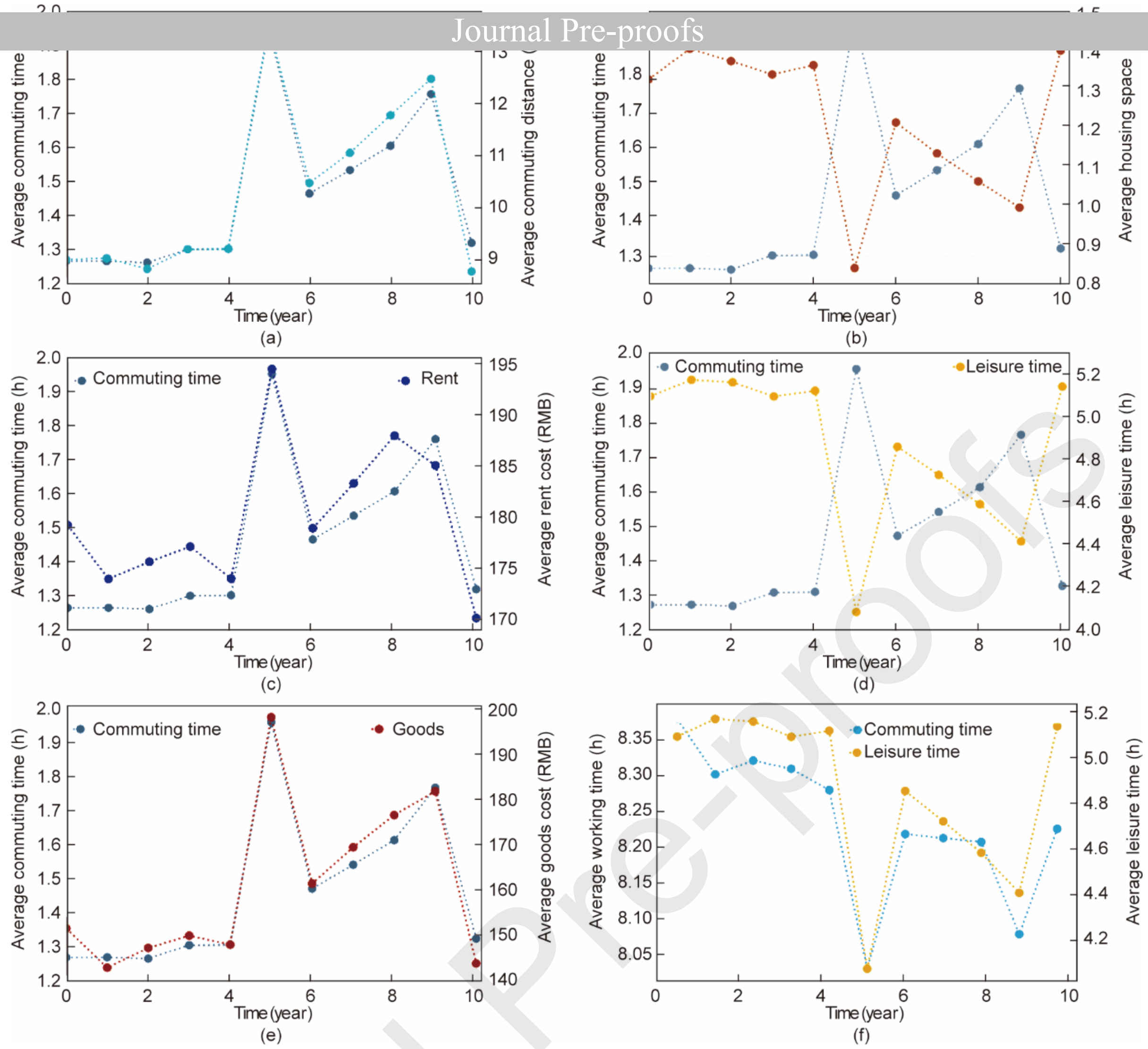

Fig. 7. Evolution of main variables. The trends in (a) commuting time and distance, (b) commuting time and housing space, (c) commuting time and rent cost, (d) commuting time and leisure time, (e) commuting time and goods cost, and (f) working time and leisure time.

This suggests an almost monotonous relationship, where greater average commuting distance tends to result in longer commuting times. Fig. 7(c) shows the rent cost for housing space, and Fig. 7(e) illustrates the non-spatial composite goods, both following a similar trend to commuting time. However, in Fig. 7(c), the rent cost does not entirely align with the changes in commuting time. For example, rent cost decreases from year 8 to year 9 while commuting time increases. This suggests that households' rent costs may be influenced by multiple factors, not solely commuting time.

The housing space in Fig. 7(b) and the leisure time in Fig. 7(d) exhibit trends opposite to those of commuting time. The increase in commuting time has led to a reduction in both working time and leisure time. As shown in Fig. 7(d), the substantial increase in commuting time in the fifth year result in a significant decrease in leisure time, exceeding one hour. In contrast, Fig. 7(f) shows that although working time also decreases concurrently, the reduction is relatively smaller, around 0.2 h. This indicates that the impact of changes in commuting time is more pronounced on leisure time, a pattern that persists even when commuting time decreases.

Fig. 8 shows the annual distributions of housing density and vehicle energy structure in urban areas. It can be observed that households with FVs tend to be located in areas closer to the CBD, and those with EVs are more likely to reside far from the center. This is because EVs have lower operational costs, and thus are more beneficial for long commuting distances. With the increase in the proportion of EVs, the range of households with FVs gradually decreases over time (i.e., the shrinking blue areas in Fig. 8), especially for the first five years.

Fig. 8 shows that households with older vehicles are concentrated close to the CBD, while those with newer vehicles tend to be located close to the periphery, which is consistent with that in Section 4.1. It suggests that the residential segregation caused by the heterogeneous agents is maintained when EVs become one potential option for commuting. Moreover, the residential density in the areas occupied by EV users tends to be low. One of the reasons for this is that the charging facility network is not yet adequately developed, which leads to much higher ICs when the residential density is high. The low residential density of EV users and the high adoption rate of EVs further result in urban sprawl. To construct compact cities while promoting EVs, it is essential to enhance the layout of the charging infrastructure in densely populated regions, thereby reducing ICs.

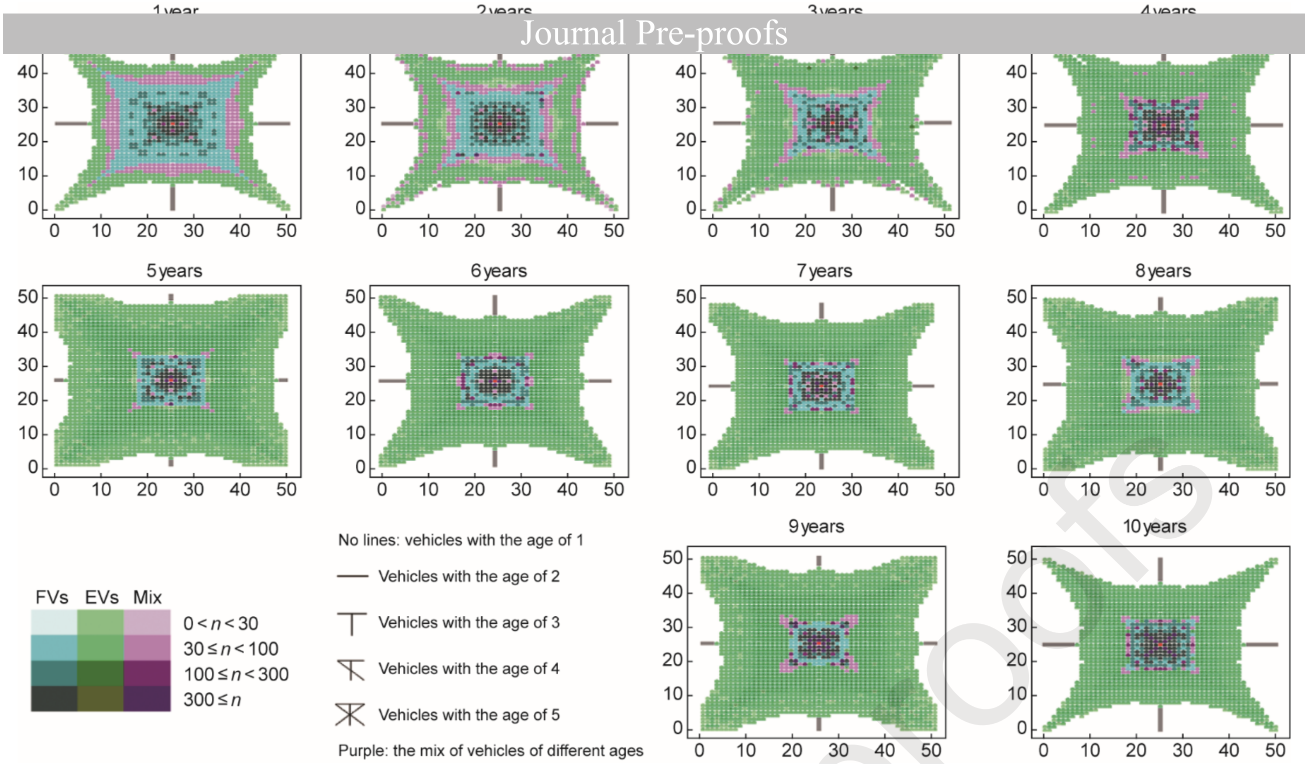

Fig. 8. Temporal evolution of urban vehicle energy and housing density structure (blue: households with FVs; green: households with EVs; purple: the mix of heterogeneous agents; darker colors mean greater density).

4.3. Factors affecting EVs adoption

4.3.1. Impacts of EV purchase price, IC, and fuel price

Fig. 9 illustrates the impact of critical factors on the adoption of EVs throughout the transition of energy sources in the automotive sector. The graph sequentially represents the proportions and influences of EV pricing, inconvenience, and the impact of gasoline fuel prices from left to right. The electricity adoption rates under different scenarios show a consistent increase from the first year to the fifth year.

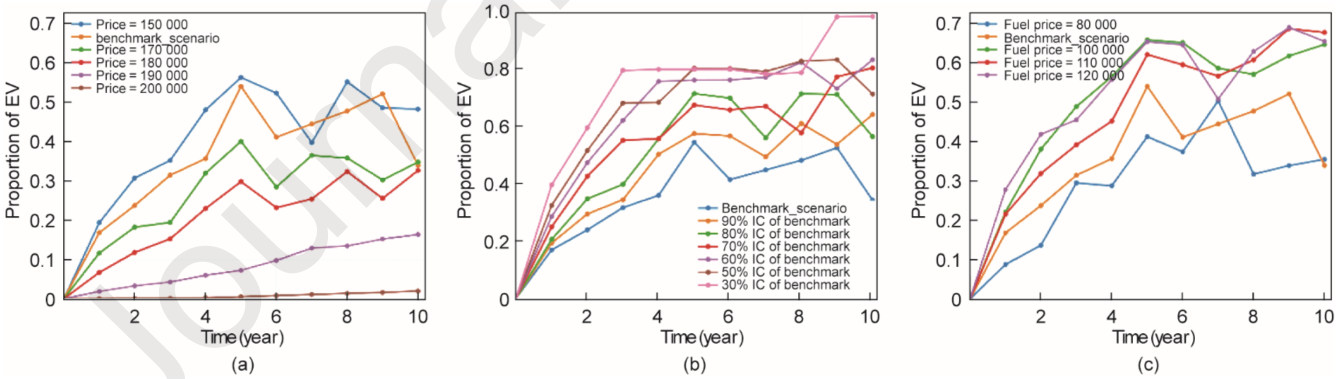

Fig. 9. Impact of main factors (a) EVs purchase price (RMB), (b) IC, and (c) fuel price (RMB) on EV adoption.

The annual evolution of the EV adoption rates under different purchase price scenarios is depicted in Fig. 9(a). Overall, an increase in the purchase price leads to a decrease in EV adoption rates, particularly when the purchase price rises from 180 000 to 190 000 RMB, where the change is especially noticeable. The electricity adoption rates show a consistent slow increase all the time when the purchase price of EVs is 190 000 and 200 000 RMB. In Beijing, as of 2023, new energy vehicles account for less than 10% of passenger cars [95]. The curve at an EV purchase price of 190 000 RMB aligns closely with this scenario, thus serving as the baseline for the comparison in Fig. 9(b). For the remaining four price scenarios, the EV adoption rates grow rapidly at the beginning. The proportion of EVs reaches its maximum value in the fifth year. After that, the EV adoption rates start to fluctuate.

Fig. 9(b) illustrates the impact of varying ICs on EV adoption. In the benchmark scenario, the proportion of EVs steadily rises, peaking at around 0.5. When the IC is halved, the adoption rate significantly increases, with the proportion of EVs nearing 0.7 by the tenth year. In the scenario where IC is reduced by 30%, the adoption rate shows an even more substantial increase, with the proportion of EVs nearing 1.0 by the tenth year. This demonstrates that reducing the IC of using EVs greatly

pro[illegible] rios. With fuel price increases, the adoption rates are higher than the benchmark, peaking just below 0.7. This indicates that higher fuel prices incentivize the switch to EVs.

Considering the current landscape, many cities and regions have attained a notable EV penetration rate of 0.10, as illustrated in Fig. 10. By comparing this with the scenario starting at zero, we observe that the established presence of EVs in the city positively affect households' inclination to choose EVs. This trend suggests that the rapid market expansion has substantially influenced the widespread adoption of EVs. While the development of a comprehensive charging infrastructure network requires time and enhancements in EV performance are constrained by technological research and development, direct economic incentives have emerged as an effective method to swiftly enhance the proportion of EVs in the city.

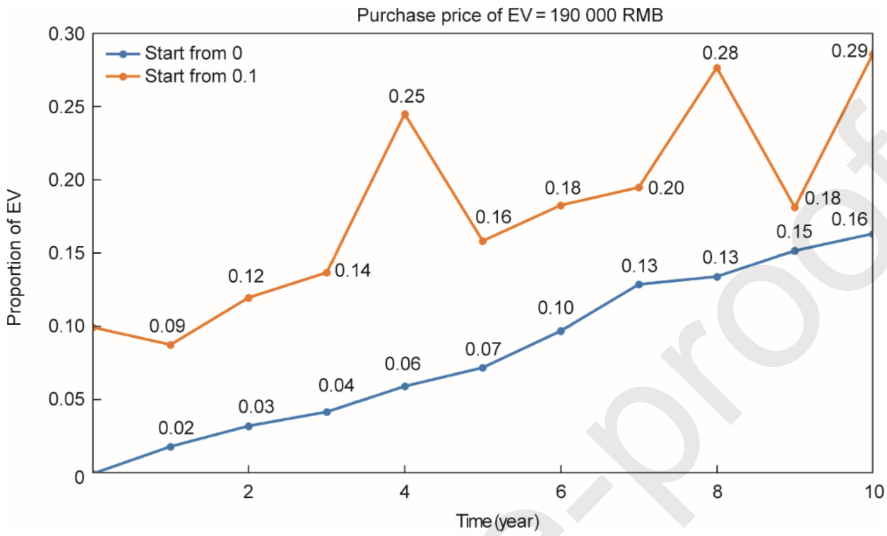

Fig. 10. Long-term impact of initial purchase incentives.

4.3.2. Impacts of public charging pile distribution

Considering the real-world distribution of charging stations, we revise the initial assumption of evenly distributing 100 charging piles per square area. Given the higher population densities and greater demand for EV charging facilities in city centers, it is more realistic to have a denser concentration of charging piles in urban areas compared to suburban or rural areas. Therefore, we adjust the model to reflect a linear decrease in the density of charging piles as the distance from the CBD increases.

We try three new different scenarios. The number of charging piles per square area from the boundary to the CBD increases from 50 to 100, 70 to 120, and 75 to 150. The result of the annual EV proportion is shown in Fig. 11.

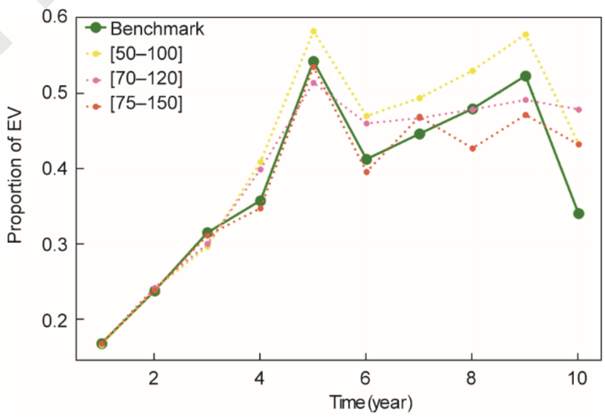

Fig. 11. Proportion of EVs over time under different charging infrastructure scenarios.

The green line represents the benchmark scenario, and the three new scenarios with denser charging infrastructure near city centers are shown in yellow, pink, and orange. The data indicate that, compared to the benchmark scenario, the increase in EV adoption in the scenarios with denser charging distribution near city centers is relatively high. In all scenarios, the proportion of EVs rises steadily over the first five years, reaching a peak around year 5, followed by a decline and fluctuations. Notably, the three new scenarios exhibit smaller fluctuations in EV adoption compared to the benchmark, suggesting that increased charging infrastructure density may help to stabilize adoption levels. Figs. 12 and 13 indicate that the residential dens[illegible] here is a shift in EV ownership patterns, with EV owners more likely to reside farther from the CBD. This shift contributes to urban sprawl, highlighting the role of charging infrastructure in shaping urban development.

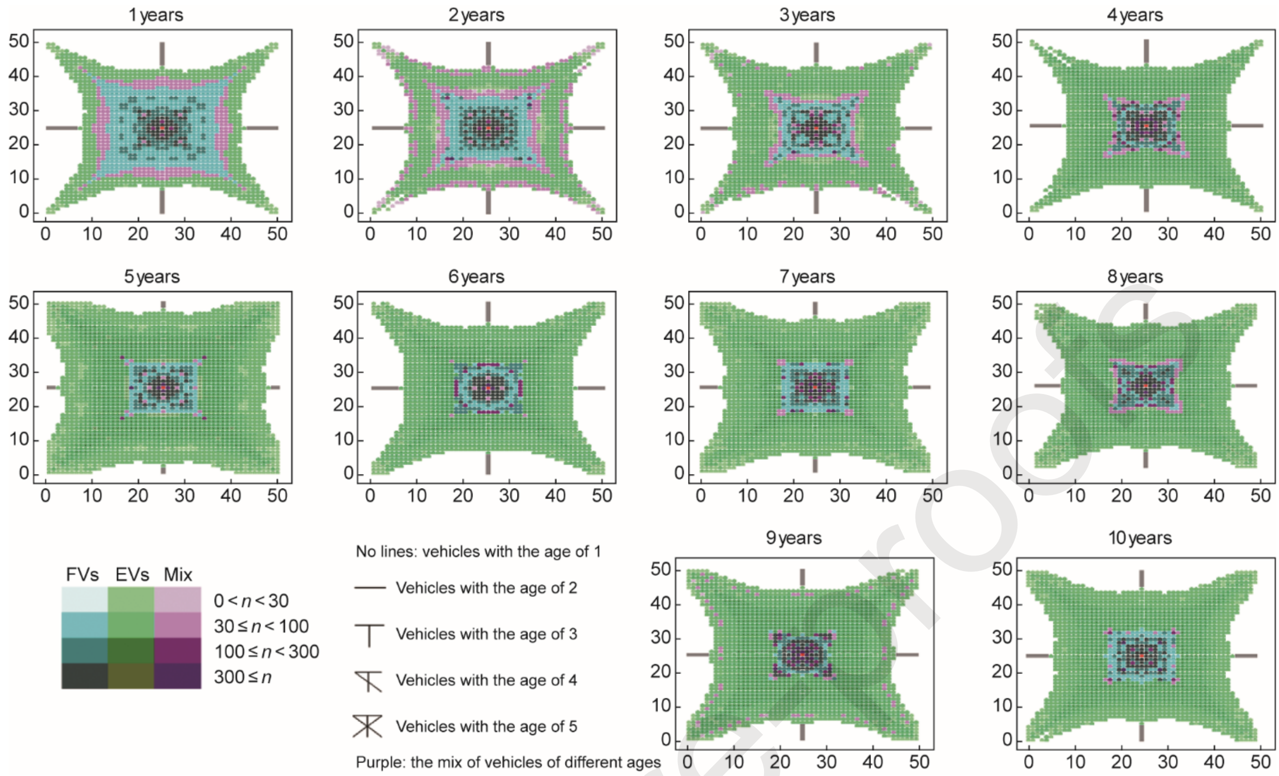

Fig. 12. Temporal evolution of urban vehicle energy and housing density structure for charging piles from 70 to 120.

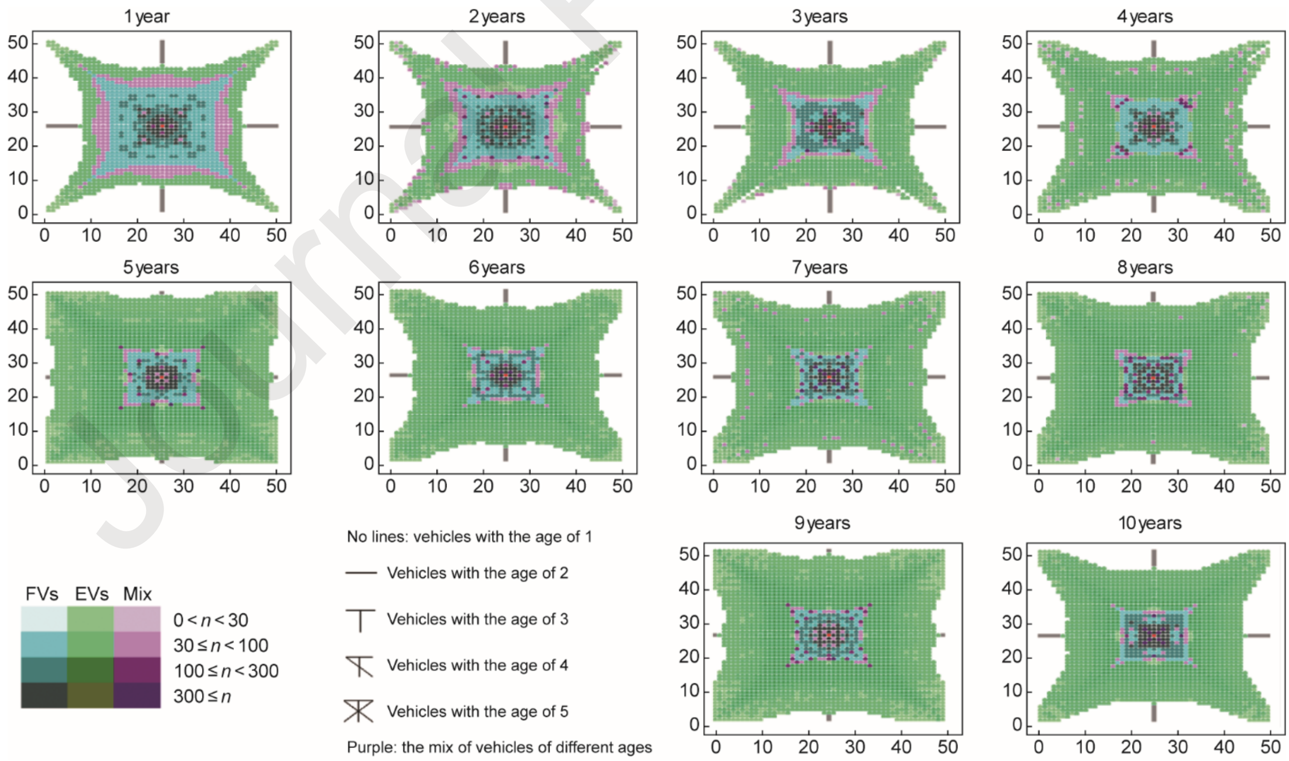

Fig. 13. Temporal evolution of urban vehicle energy and housing density structure for charging piles from 50 to 100.

The minimal effect of charging pile distribution changes on households' choice of vehicle energy type could be attributed to the large number of charging piles, which reduces competition among EV owners. Figs. 12 and 13 illustrate that residential density in the EVs distribution area is relatively low, with the corresponding green areas appearing lighter in color and most parcels containing fewer than 100 people, with some even below 30. As a result, the ratio γ in Eq. (18) is nearly zero, making it to acks of driving range anxiety rather than the competition for charging piles. To verify the above analysis, we conduct simulations of low-density charging piles. We found that the density of charging piles begins to affect the proportion of EVs when the number of charging piles is below 20 per square area (Fig. 14).

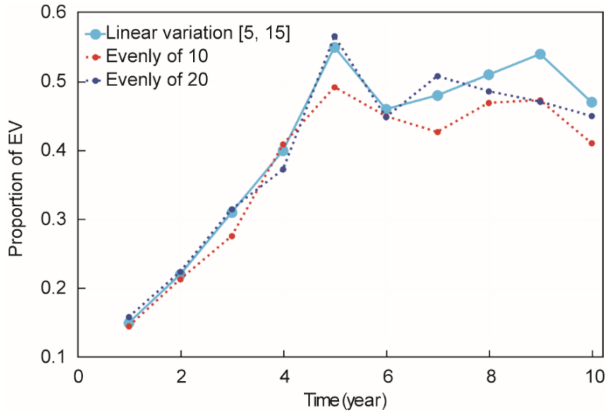

Fig. 14. Annual trend in EV Proportion with low charging pile density.

Fig. 14 shows that with 20 charging piles per parcel, the EV proportion remains similar to the benchmark scenario. However, when reduced to ten charging piles per parcel, the EV proportion drops significantly from the fifth year onward, consistently staying lower than in the 20-charging pile scenario. The blue line represents the scenario where the density of charging piles decreases linearly from 15 near the center to 5 at the periphery. Since fewer parcels near the CBD, the total number of charging piles in this scenario is lower than in the scenario with ten charging piles evenly distributed per parcel. Despite this, the proportion of EVs is significantly higher.

As shown in Table 3, there is a positive correlation between households' commuting distance to the CBD and the proportion of EVs, mainly because the share of EVs with longer commuting distances increases. After the fifth year, as the EV market approaches saturation, the average commuting distance of EVs trends similarly to the proportion of EVs. Typically, a higher proportion of EVs is associated with longer commuting distances, likely due to urban expansion. When comparing two charging pile layouts, one with ten piles per parcel and another with a decrease from 15 near the center to 5 at the periphery, we find that the latter generally leads to shorter commuting distances for EVs, even with similar EV proportions. For example, in the fifth year of case 1, the EV proportion is 0.49 with a commuting distance of 21.32 km, while in the eighth year of case 2, the EV proportion is 0.51 with a shorter distance of 20.83 km. Similarly, in the sixth year, the EV proportion in case 1 is 0.45 with a distance of 21.05 km, compared to 0.46 and 20.22 km in case 2.

These findings suggest that a layout with denser charging infrastructure near the city center, as shown in case 2, tends to shorten commuting distances for EVs, encouraging their use closer to the CBD.

Table 3
Comparing different charging pile distributions.

Year	Evenly of 10 (case 1)			Linear variation [5, 15] (case 2)		
	Proportion of EVs	Average distance (km)	EVs' average distance (km)	Proportion of EVs	Average distance (km)	EVs' average distance (km)
1	0.14	9.02	22.42	0.15	8.98	21.92
2	0.21	9.04	21.02	0.22	8.88	20.32
3	0.28	9.18	20.15	0.31	9.43	20.31
4	0.41	11.56	21.24	0.40	10.81	20.36
5	0.49	12.79	21.32	0.55	13.87	21.30
6	0.45	11.79	21.05	0.46	11.43	20.22
7	0.43	11.32	20.53	0.48	11.92	20.35
8	0.47	12.31	21.04	0.51	12.85	20.83
9	0.47	12.42	21.41	0.54	13.78	21.38

While our simulation provides serval insights into the impact of EV adoption on urban residential patterns and energy consumption, it has certain limitations. By keeping key EV parameters such as battery capacity, purchase price, and electricity consumption rate constant, the model allows for a focused analysis of depreciation costs associated with vehicle aging. However, as technology progresses, improvements in charging infrastructure, faster charging times, and increased vehicle range are expected to mitigate these limitations, making EVs more viable and accessible for widespread adoption. The model does not account for potential technological advancements that could influence these parameters over time, and future studies should be given on these.

5. Conclusions and future studies

This study proposes a spatial equilibrium to analyze the interactions between household vehicle energy type choices and residential location choices. We study household adoption of EVs and urban structure over time by analyzing the difference in commuting costs between EVs and FVs and the impacts of vehicle age. The proposed model offers a novel perspective on the dynamic interactions between EV adoption and urban development, a topic that has been underexplored in previous research. Our study shows that households with FVs opt for locations closer to the CBD, whereas those with EVs are dispersed farther from the CBD. Furthermore, households with older vehicles tend to be on the periphery of the same vehicle category.

Regarding urban density structure, our research suggests that heterogeneity in vehicle age contributes significantly to urban sprawl and congestion. Residential segregation divides the city into concentric rings, hindering individuals residing in outer residential rings from aggregating towards the city center. In addition, the residential density decreases with distance from the CBD within each residential ring. This phenomenon generates a pattern wherein high-density residential areas encircle low-density residential areas within a city, worsening congestion. This aligns with the existing research findings. For instance, Li et al. [105] report that cities shaped like a mountain, with taller buildings in the center, have less traffic congestion, whereas those with a Basin layout or flat sprawl suffer more severe congestion.

While this study offers valuable insights into the interactions between EV adoption and urban development, several limitations should be noted. Firstly, the research primarily focuses on dense urban areas without fully considering the crucial role of home charging stations in the widespread adoption of EVs. Future studies should be conducted to explore the impacts of home charging infrastructure on shaping EV adoption and residential choices. Moreover, this study analyzes the impacts of aged vehicles on ownership costs without considering the development of EV technology. However, the rapid development of EV technology may significantly change the battery capacity and the charging duration, largely lowering the expenses of EVs. Therefore, the impacts of battery and charging infrastructure technology development should be considered in the future. In addition, the overloading of the electricity system during peak hours may reduce the charging reliability and quality of EVs, leading to uncertainty in electricity supply. Future studies should be conducted to explore the roles of smart charging control strategies and home energy systems in reducing the ICs of owning EVs.

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Compliance with ethics guidelines

Chao Shu, Yue Bao, Ziyou Gao, and Zaihan Gao declare that they have no conflict of interest or financial conflicts to disclose.

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