Vol. 35, No. 1 (2025) | DOI: 10.37190/ord250103

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Operations Research and Decisions

www.ord.pwr.edu.pl

OPERATIONS RESEARCH AND DECISIONS QUARTERLY

Everyone is different, but does it matter? The role of heterogeneity in empirically grounded agent-based models of alternative fuel vehicles diffusion

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Abstract

There is a large literature on agent-based models (ABMs) to study the diffusion of alternative fuel vehicles (AFVs). Potentially, ABMs could be used to design policies that effectively promote AFVs. Unfortunately, ABMs have several drawbacks related to their complexity – models that are too simple are unrealistic, and models that are too complicated are difficult to describe, verify, and validate. Here we investigate what level of complexity is needed. We focus on the issue of heterogeneity because it is one of the biggest advantages of ABMs, but also one of the main sources of complexity. We begin with a brief review of ABMs for AFV diffusion. We then generalize an empirically grounded ABM of AFVs to analyze the role of different types of heterogeneity related to individual characteristics and social network structure. We show that most of these heterogeneities do not affect the outcome of the model. To facilitate replication of our results, we describe the model and its calibration to empirical data in detail. We also provide a link to a public GitHub repository where the code files, empirical data, and scripts are uploaded to analyze the results.

Keywords: *agent-based model, alternative fuel vehicles, battery electric vehicles, plug-in electric vehicles, hybrid electric vehicles, simulation, diffusion, consumers*

1. Introduction

Transport is a major source of greenhouse gases and local air pollutants. Health, economic, and social costs of local air pollution are significant, ranging from reduced life expectancy and increased infant mortality to far-reaching economic consequences such as job losses or reduced consumer spending [15, 55]. The

Received 11 October 2024, accepted 16 November 2024, published online 8 February 2025
ISSN 2391-6060 (Online)/© 2025 Authors

The costs of publishing this issue have been co-financed by the Department of Operations Research and Business Intelligence at the Faculty of Management, Wrocław University of Science and Technology, Wrocław, Poland

European Low-Emission Mobility Strategy emphasizes the need to decarbonize the transport sector and to reduce emissions in this sector, especially in urban areas.

The European Green Deal aims to reduce greenhouse gas emissions by 90% by 2050. Moving to more sustainable transport means putting users first and providing them with more affordable, accessible, healthier, and cleaner alternatives [23]. A key goal is to significantly increase the use of alternative fuel vehicles (AFVs). Among most popular alternatives for conventional cars running on petrol or diesel, classic hybrid electric vehicles (HEVs), plug-in electric vehicles (PHEVs), and battery electric vehicles (BEVs) or hydrogen fuel cell vehicles (HFCVs) are included [50]. While the AFV market share continues to grow worldwide, its smooth diffusion faces many barriers, including a lack of sufficient charging infrastructure, high prices, limited range of batteries, and security issues [24, 53, 58, 59, 88].

Certain political and strategic actions are needed to accelerate diffusion and increase social acceptance and market share. This topic has been recently widely researched using various methods such as an analysis of the market data [29, 42, 64, 66], stated preference methods, for example, discrete choice experiments [11, 34, 35, 48, 54], or conjoint analysis [25, 47, 51, 94]. Most of these studies investigate consumers' preferences toward AFVs and explore the potential incentives and barriers to further market growth.

Although these studies shed some significant light on the identification of factors responsible for further AFV market penetration, they do not allow us to study how social influence and various external factors, like education, marketing campaigns, or political tools, can enhance the diffusion. For such a what-if analysis, agent-based models (ABMs) seem to be a particularly useful tool. ABMs can be defined as models where individuals or agents are described as unique and autonomous entities that usually interact with each other and their environment locally [68]. They are often treated as computational laboratories because they allow us to simulate some changes at the macroscopic level resulting from the interactions between the heterogeneous agents (e.g., consumers, households, producers, etc.) at the microscopic level [81]. ABMs have been used in various aspects of marketing, e.g., consumer choices [49], supply-side diffusion in industries [18], diffusion of innovation [20], etc. In this paper, we focus on the consumer choices related to AFVs.

According to [22, 81], the best ABMs are based on real-world data sets, which allow us to derive real-world agent attributes and calibrate the entire model setup. We want to emphasize that this should be treated as one of the opinions in the world of agent-based modeling enthusiasts, rather than as a general belief. Which type of model is best depends mainly on the purpose of the model. Simple, theoretical ABMs are very useful for facilitating theory building, exploring general questions, serving as illustrative examples and narratives, and discovering general rules about causal relationships [84]. On the other hand, empirically based ABMs are better suited for case-specific analysis and decision support because they can be tailored to specific problems and stakeholders. However, the problem is how to incorporate empirical data into such models, in our case, ABMs of AFV diffusion. As recently noted, most of the literature does not specify in detail how to incorporate individual user behavior into an ABM [30]. This is a particularly relevant issue in the context of ABMs, as they are often criticized for not being a rigorous research tool [9, 69].

One of the main problems associated with ABMs is the widespread lack of a sufficiently detailed model description to allow re-implementation and subsequent replication of results by other researchers [32]. Another problem is the lack of rigorous sensitivity analysis of such models [9], i.e., what if the empirical data used are inaccurate and our model is extremely sensitive to their change? Both of these problems are directly related to the complexity of the model. For simpler models, both description and sensitivity analysis are easier. On the other hand, simpler models may be unrealistic. Finding the optimal level of complexity is a fundamental problem [33]. Therefore, the goal of this paper is to show how to rigorously determine whether a given level of model complexity at the microscopic level (agents) adds anything new to the model in the context of macroscopic results (level of adoption in society, market share, etc.). We will focus on the issue of heterogeneity because the ability to account for heterogeneity is one of the major advantages of ABM.

It is obvious that any social system, including the market for AFVs, is heterogeneous in many ways. Each consumer has certain unique preferences. The social network of consumers is also heterogeneous. But do these various heterogeneities affect the macroscopic behavior of the system? This question was the direct inspiration for this work. We are not the first to ask this question. A systematic analysis of the role of heterogeneity has been done previously for the SEIR (susceptible-exposed-infected-removed) model [67]. However, to our knowledge, such a question has never been asked for ABMs of AFV diffusion.

In our previous paper, we proposed an empirically grounded ABM of AFV diffusion [41]. All agents in this model are identical, i.e., they have no individual characteristics. Furthermore, the model was considered on the square lattice, meaning that each agent had exactly four neighbors. Thus, the system was homogeneous in terms of agent characteristics and network structure. In this work, we generalize the model so that we can analyze the role of different types of heterogeneity, such as individual susceptibility to marketing, local and global social influence, or an individual driving pattern. We estimate the values of all these individual characteristics based on survey responses previously used for conjoint analysis [51]. We also apply the model to several networks, ranging from homogeneous to heterogeneous. We systematically compare the homogeneous and heterogeneous versions of the model. As a result, we determine which types of heterogeneity affect the model's results.

The remainder of the paper is organized as follows. In Section 2, we briefly review the goals of AFV diffusion ABMs and outline the obstacles that may hinder the achievement of these goals. In Section 3, we describe possible sources of heterogeneity in ABMs and briefly review what types of heterogeneity can be found in ABMs of AFV diffusion. In Section 4, we describe our model and the calibration procedure in detail. We also provide a link to a public GitHub repository where the code files, data, and scripts used to analyze the results are uploaded. All this should facilitate the replication of our results, which is a key of the scientific approach [32, 68]. In Section 5, we describe the results, and finally, we conclude our work in Section 6.

2. Purpose of agent-based modeling of AFV diffusion

ABMs of AFV diffusion have already been reviewed in several articles. For example, ABMs focusing on market forecasts in the field of electric mobility have been reviewed in [2]. The comparison of various research methods and their outcomes let the authors conclude that modeling of AFV market penetration rate should combine consumer surveys with modeling of producers' decisions regarding the type and amount of cars they want to supply as well as with modeling of governmental policies with its effect on the supply side of the market. The review of Bustos and Turu classifies models according to their spatial and temporal scale, agents' attributes and behavior, and focus areas (e.g., market, planning and operation, etc.) [13]. Next, Gnann and Ploetz reviewed combined models for market diffusion of AFV and their refueling infrastructure [29]. The work of Zhang and Vorobeychik does not refer directly to AFV diffusion models, but the outcomes of the analysis are valid for AFV market penetration models. The authors pay main attention to various calibration and parameterization techniques used in agent-based modeling of innovation diffusion. Finally, the empirically grounded ABMs of innovation diffusion have been recently reviewed in [73] and [93]. The latter has categorized ABMs along two dimensions: methodology and application. Therefore, we do not provide a regular review in this paper. Instead, we focus on reviewing the purposes of ABMs of AFV diffusion (see also Table 1) and describing the obstacles that may hinder the achievement of these goals.

Table 1. Purpose and usage of empirical data of the chosen ABM for AFV diffusion

Purpose	Source of data/method used	Reference
To explore how policies may interact with consumer behavior over a long time period	Detailed data of $N = 1795$ respondents have been used to parameterise the agents and to addresses different consumer needs and decision strategies	[43]
To explore effectiveness of roll-out strategies of charging stations in the context of BEV diffusion	Empirically observed charging patterns behaviors and 2 million actual charging sessions from the city of Amsterdam are used	[90]
To replicate real-life BEV use and its impact on network demands	consumers' patterns of charging behaviour and its impact on the peak demand are included in the ABM calibtration	[52]
To investigate the effect of agents' decision-making processes at the microlevel into the number of adopted BEV at the macrolevel	twitter data analytics are used to investigate information engagement coefficient based on agents' locations	[61]
To investigate consumers' behaviors regarding BEV and PHEV under various scenarios	Data derived from a choice-based conjoint study	[47]
To simulate market acceptance of BEV under multi policy scenarious	parametrization is based on the literature review	[37]
To understand the consumers' adoption decision-making and to explore potential policy interventions favoring the uptake of NGVs	calibration of the adoption threshold and propensity to media influence is based on real data from a field survey	[80]
To simulate the effects of policy interventions and social influence on consumers' transport mode preferences	attributes of the agents are derived and calibrated from the survey	[91]
To calculate time-dependent market share of each AFV technology, taking into consideration the utility of each type of a car and WTP of the consumers	real-world, individual driving data are used instead of average driving patterns	[66]

The majority of ABMs explore AFV diffusion under various scenarios and measure the adoption rate at the macro-level. Some studies investigate multiple categories of AFVs, such as HEVs, PHEVs, or BEVs [41, 46], whereas others focus on PHEVs separately [17, 26] or together with BEVs [10, 29, 37, 47, 76] or investigate BEVs specifically [16, 56, 61]. Most of the studies include also conventional vehicles (CVs) in the trade-off that consumers face.

Such models simulate under various conditions whether agents decide to shift to alternative vehicles or continue buying an ordinary (i.e., conventional) car [80]. In [80], an ABM is also used to explore the effectiveness of policy options on the diffusion of vehicles fueled by natural gas (NGVs). At the same time, the examination of fuel cell hydro vehicles (FCHVs) using ABMs is still rare [63, 95].

Sometimes the attention of researchers is focused not only on AFV diffusion but on the development of charging stations as a necessary part of the infrastructure needed for the successful diffusion of AFVs [52, 90]. Such ABMs explore roll-out strategies of charging stations and their impact on further BEV diffusion. Many studies include scenario analysis to compare the results dependent on some internal or external parameters.

For example, in [90], different scenarios related to the type of charging infrastructure and the intensity of rollout are explored. In [52], the authors aim to identify the impact of BEVs on the local grids. Their ABM is built based on the real data, which include consumers' charging behavior and its impact on the peak demand. Other models focus on the market acceptance of AFVs under various scenarios [37] or consumers buying behaviors [47].

In the variety of ABMs exploring the market of AFVs, generic models applicable for any country or region [37] or specific models, which are designed and calibrated for a given part of the world, can be found. For example, the models of [12, 29, 46] propose simulations for Germany, whereas the model of [61, 80] are built for the Indonesian automotive market. An ABM proposed by [43] is designed for the Dutch market. Other models explore automotive markets in South Korea [17], the USA [10, 26, 79, 86, 94], Ireland [56], Iceland [76], or China [37]. Other models present the conditions for a specific city like Amsterdam [90], New York [1], or Berlin [91].

A lot of research focuses on the impact of governmental policies, such as subsidies or tax exemption, and their interaction with consumer behavior over a long time period [12, 37, 43, 80, 90, 91]. . In particular, authors want to verify which policies most effectively facilitate the transition from conventional into electric vehicles and what combinations of policy measures, strategies, and targets are the most effective in facilitating adoption of BEVs and lowering the emissions [12, 43]. Other models explore the effect of different policy interventions on the adoption and diffusion of a given alternative fuel vehicle (such as NGVs in [80] or BEVs in [12, 91]).

Many models investigate various scenarios differing by monetary or non-monetary incentive, like in [37], where the authors explore how to promote conversion from CVs to BEVs through a scenario-response method. Sometimes different policy scenarios are simulated against a business as usual scenario [12]. The work of [76] forecasts the differences in BEV diffusion under different pricing regimes. The developed ABM in [90] is used to evaluate three case studies designed and calibrated for the city of Amsterdam, which address prominent questions by policymakers, referring to charging infrastructure deployment (that is, how many and which type of charging stations should be placed where). The InnoMind model of [91] simulates effects of policy interventions and social influence on consumers' transport mode preferences.

Considering all of the above objectives, ABMs of AFVs could be and sometimes are recommended as a decision support tool to evaluate potential policy recommendations [80]. The results and conclusions may give some guidelines how to promote AFVs effectively as well as how many of the charging stations and where should be installed [90]. Unfortunately, several obstacles may hinder the usage of ABMs as a scientific tool. In the context of social ABMs, the necessity for verification, validation, or sensitivity analysis is often reported [2, 9, 69]. However, something that absolutely discredits the model as a scientific method is the inability of other researchers to replicate the results [32, 68]. Most of the literature does not describe either the model nor the calibration method in detail [30]. This is not very surprising, as ABMs are often very complicated and thus difficult to describe in sufficient detail. While the Overview, Design concepts and Details (ODD) protocol for describing ABMs has been proposed and widely accepted, it has some limitations [32]. What would definitely facilitate both the description and the other elements of a rigorous approach would be to simplify the model. However, there is a concern that simplification comes at the cost of making the results less realistic. Therefore, it is desirable to build models in so-called Medawar zone, which is the region of maximum usefulness as a function of model's complexity [33, 84]. One of the main sources of an ABM's complexity is heterogeneity, which can appear on different levels. Hence, the next section is devoted to heterogeneity in ABMs of AFV adoption.

3. Heterogeneity in ABMs of AFV adoption

According to the definition of an ABM quoted in the Introduction, agents are unique and autonomous entities that interact locally with each other and with their environment. Being unique means that agents can differ from each other in many ways, such as personal characteristics, preferences, location, etc. Being autonomous means that agents make decisions and are independent of each other. Finally, interacting locally means that agents often do not interact with all other agents, but only with their neighbors in some kind of space (geographic or/and social) [68]. Heterogeneity can be introduced in all three aspects of ABMs.

The ability to account for heterogeneity among agents, allowing for the representation of different preferences, constraints, and behaviors, is often considered one of the most important features of agent-based models, distinguishing them from approaches based on differential equations [31, 67]. This can be particularly important in the context of AFV diffusion, as different types of consumers may have different motivations and barriers to adoption. For example, some consumers may prioritize environmental concerns, while others may be more influenced by economic factors or convenience. By introducing heterogeneity into agent-based models, researchers can better understand the complex processes that drive AFV adoption and identify potential leverage points for promoting the diffusion of this technology.

A popular approach is to individualize the agents themselves, giving them different socio-demographic characteristics such as age, income, and affinity for innovation [12, 26, 76]. In [29, 65], the authors investigated the impact of individual driving patterns, modeling customers with different transportation needs. An interesting personal trait, named level of rationality, was introduced in [26]. It determined the ability of an agent to estimate fuel cost saving while choosing a new vehicle.

One could also heterogenize the vehicle space, allowing agents to choose not only from broad categories such as CVs, PHEVs, BEVs, etc., but also from different segments [19], size classes [29, 65], engine parameters [19] with different fuel economy, depreciation value [43], and so on. This is most often used in conjunction with heterogeneous agents, resulting in models with multiple levels of heterogeneity. Going even further, in [90], authors try to capture consumer behavior with respect to charging infrastructure, which may be different for residents, visitors, taxis, and shared vehicles.

In order to ground the models in reality and set realistic values of parameters, the usually employed approach is to precede ABM simulations with an empirical study, which will provide the data necessary for setting the parameters of the model. Afterward, researchers can either use the aggregated attributes [56], or create a one-to-one correspondence between survey respondents and agents in the simulation [43, 91].

While it is argued that this approach allows for more realistic simulations and can provide valuable insights [5, 67, 87], it also introduces new challenges and limitations. One potential danger is the inevitable increase in the number of parameters and the risk of overfitting [84]. The model becomes too complex and difficult to interpret. This can happen if too many agent characteristics are included in the model, resulting in a large number of parameters (each requiring an empirical distribution) that may be difficult to estimate or justify. Overfitting can also lead to unstable or unreliable results as the model becomes sensitive to small changes in the input data [82]. This in turn makes proper validation, calibration, and interpretation difficult. On the other hand, a complete lack of heterogeneity creates the risk of oversimplification, which can occur if the model includes only a limited set of agent characteristics or behaviors, or assumes that all agents are homogeneous in their behavior. In such cases, the simulation may not accurately reflect the diversity and variability of real-world agents, leading to misleading conclusions [84].

Another type of heterogeneity concerns the space (geographic and/or social) in which agents interact. Typically, this space takes the form of a graph. Most models assume that each agent (i.e., a consumer) is part of its social network, where it is connected to other agents who live nearby and/or some agents who are more distant but have similar attributes (e.g., income [80] or environmental attitudes) or belong to a similar group of vehicle owners (i.e., BEV owners). For example, in [37], the Watts–Strogatz (WS) small-world graph was used to describe the structure of the consumer interaction network. In [41], a square lattice with periodic boundary conditions was used, which can be interpreted as a geographic space. In such a graph, each agent has exactly four neighbors, as opposed to a WS network where the number of neighbors can vary for each agent. However, even in such a regular graph, there is heterogeneity in space because each agent has different neighbors. For example, one agent may have only HEV consumers in the neighborhood, while others may have only PHEV consumers, which can have a significant impact on a consumer's decision.

4. Model description and setup

Our agent-based model represents an automotive market with three categories of alternative fuel vehicles: HEVs, PHEVs and BEVs. Agents are consumers, they can mutually interact via links in a social network (Section 4.1). Vehicle purchase decisions are governed by a discrete choice model, which relies on utility theory [2] (Section 4.2). Additionally, the model takes into account three important factors that impact the diffusion of eco-innovations: marketing, social influence, and external barriers [14, 64].

We set the model parameters based on the empirical data derived from a survey and a conjoint study [51] (Section 4.3). The simulation code and the empirical data used in the simulations are publicly available (Section 4.4). The procedure for calibrating the model is described in Section 4.5.

4.1. Social network

We consider a population of N agents (consumers) placed in the nodes of a given network. In general, our model can run on any network. However, we use two structures, a square lattice with periodic boundary conditions and the Watts–Strogatz (WS) network [89]. A square lattice serves as a reference point since it was used in the original study [41]. This structure can also represent the geographic space. In such a network, each consumer is directly connected to four others, which means that the degree of each node is equal to four. On the other hand, the WS graph allows us to model a wider range of structures. This network is parameterized by the average node degree $\langle k \rangle$ and the rewiring probability β, which describes the level of randomness. By changing the rewiring probability β, networks of different characteristics can be constructed, from regular lattices ($\beta = 0$) to random graphs ($\beta = 1$) (Figure 1). Small-world networks, which share some features with the real social networks, fall between these two extremes [3].

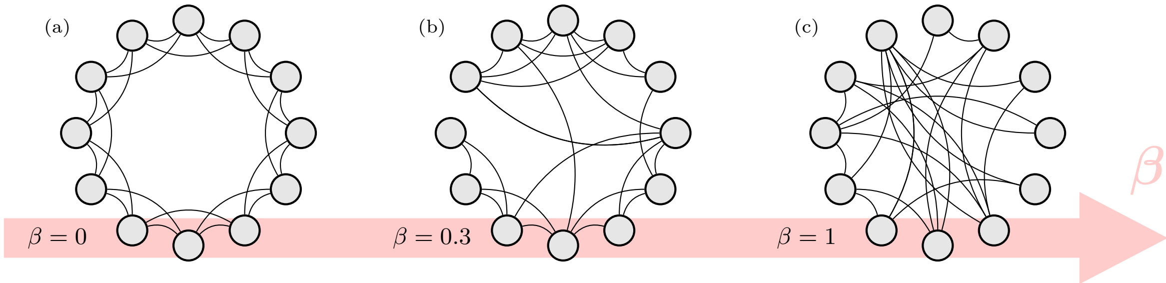

Figure 1. Illustration of the Watts–Strogatz networks with $N = 12$ nodes, $\langle k \rangle = 4$, and three different values of β. The very left structure ($\beta = 0$) is a regular graph, whereas the very right represents a random graph ($\beta = 1$).

4.2. Discrete choice model

Each agent can have a car. However, agents start the simulation without cars. At each time step, a randomly selected agent buys a car chosen from the set of alternative fuel vehicles that is taken from the conjoint analysis [51] of data collected between January and April 2020. The vehicles are characterized by five attributes, each of which can take five different values. Therefore, we have 25 variants of cars in each of the three categories: HEV, PHEV, and BEV, for a total of 75 variants of cars labeled by $j \in \{1, 2, \ldots, 75\}$. For the sake of brevity, we will use an interchangeable variant of a car, or just a car. However, it is important to remember that we are considering not just 75 cars, but 75 variants of cars. According to [51], for HEV, the attributes are safety level, purchase price, access to service, functionality level, and car type, whereas for PHEV and BEV, these are safety level, purchase price, access to service, access to charging, and range. Tables with profiles of all cars were presented in [51]. We have also included them in Appendix A (Tables A1–A3) of this paper for convenience.

Each attribute contributes to the total utility that comes from purchasing a given car. To obtain the total utility of the car j, we sum the partial utilities associated with the attributes of this car:

$$U_j = \sum_{n=1}^{5} PU_{j,n}, \tag{1}$$

where $PU_{j,n}$ is the partial utility of the nth attribute of a variant j. Partial utilities were estimated based on the conjoint analysis of consumers' preferences (Table 14 in [51]) for the exact values. We have also included this data in Appendix A (Table A4) for convenience.

In addition to the total utility, we consider three environmental factors that impact the agents' buying decision: marketing, social influence, and the availability of recharging facilities. To connect these factors with the probability of choosing a car over all alternatives, we use a discrete choice model based on a multinomial logit function [2]. In studies on AFV diffusion, logit models are not only incorporated into agent-based simulations as discrete choice models [2, 62, 77, 83, 92, 94], but are also commonly used to estimate consumers' preferences based on survey data [7, 11, 34, 64, 72, 94]. Following previous studies [41, 60, 75, 76], the probability that agent $i \in \{1, \ldots, N\}$ buys a car j has the following form:

$$P_{i,j} = \frac{W_{i,f(j)} RFE_{i,f(j)} \exp\left(U_j\right)}{\sum_{k=1}^{75} W_{i,f(k)} RFE_{i,f(k)} \exp\left(U_k\right)}, \tag{2}$$

where function

$$f(j) = \begin{cases} \text{HEV} & \text{if the } j\text{th car is HEV} \\ \text{PHEV} & \text{if the } j\text{th car is PHEV} \\ \text{BEV} & \text{if the } j\text{th car is BEV} \end{cases} \tag{3}$$

returns the category of a car, whereas $W_{i,f(j)}$ and $RFE_{i,f(j)}$ are variables associated with agent i that reflect its willingness to buy a car of a given category and the refueling effect, respectively.

The idea of willingness appears in [44, 45, 62, 77, 83] where the system dynamics approach [78] is used to study the adoption of AFVs. Therefore, the willingness, which depends on the marketing and social exposure to the product, is modeled as a set of differential equations. Recently, we have adapted this idea to agent-based modeling [41]. In our approach, the willingness to buy a given car also arises from marketing and social influence, but it does not have a differential form. Furthermore, since empirical studies show that the strength of social influence between people depends on their proximity in the social network [64], we distinguish between two types of social influence, local and global one [39, 41, 56, 57]. Local social influence corresponds to word-of-mouth marketing, e.g., recommendations from friends who have already purchased an AFV. On the other hand, global social influence reflects the tendency of agents to adhere to social norms, e.g., following the trend seen on the streets. Thus, the adoption of AFVs increases along with more evidence that other people have adopted them [64]. How much these factors influence the willingness depends on individual traits of agents. Let $p^{\text{adv}}_{i,f(j)}$, $p^{\text{local}}_{i,f(j)}$, and $p^{\text{global}}_{i,f(j)}$ denote the susceptibilities of agent i to advertisement (or other types of marketing), local influence, and global influence related to a given type of vehicle. Since we consider three vehicle types, each agent is characterized by 9 susceptibilities, which are set at the beginning of the simulation. The willingness of agent i to buy a car of type $f(j)$ is expressed by the following equation:

$$W_{i,f(j)} = \underbrace{p^{\text{adv}}_{i,f(j)} h_{f(j)}}_{\text{marketing}} + \underbrace{p^{\text{local}}_{i,f(j)} k_{i,f(j)}/k_i}_{\text{local influence}} + \underbrace{p^{\text{global}}_{i,f(j)} N_{f(j)}/N}_{\text{global influence}} + \underbrace{1}_{\text{independence}} \tag{4}$$

where $h_{f(j)}$ reflects the strength of marketing for vehicle type $f(j)$, $k_{i,f(j)}$ is the number of neighbors of agent i that already possesses vehicles of type $f(j)$, k_i is the total number of neighbors of agent i, and $N_{f(j)}$ is the total number of agents in the system that have vehicles of type $f(j)$. The first term in the above equation captures the influence of advertisements and promotions. The second one reflects the local influence by which an agent is more likely to buy a car of a given type if a greater fraction of his neighbors have already adopted it. The third term corresponds to the global influence by which an agent is more likely to buy a car of a given type if greater fraction of the population has already adopted it. Finally, the last term accounts for independent behavior since when all susceptibilities are zero, $W_{i,f(j)} = 1$, so the decision is made only based on the car utilities and the refueling effect, see equation (2).

The refueling effect captures agents' concerns about low ranges of some AFVs and the availability of recharging facilities. We include this effect in a functional form taken from previous studies [41, 60, 74–76]:

$$RFE_{i,f(j)} = \begin{cases} 1 & \text{if the } j\text{th car is HEV} \\ 1 - DP_i \mathrm{e}^{-\alpha_{\text{PHEV}} N_{\text{PHEV}}/N} & \text{if the } j\text{th car is PHEV} \\ 1 - DP_i \mathrm{e}^{-\alpha_{\text{BEV}} N_{\text{BEV}}/N} & \text{if the } j\text{th car is BEV} \end{cases} \tag{5}$$

where DP_i is an individual driving pattern of agent i, N_{PHEV} and N_{BEV} are the numbers of agents that have already adopted PHEVs and BEVs, while α_{PHEV} and α_{BEV} are scaling parameters used to calibrate the model. Driving patterns vary between 0 (short trips) and 1 (distant trips) [74]. Note that $RFE_{i,f(j)}$ for electric vehicles (PHEV and BEV) depends on the number of adopted agents–the more agents adopt electric vehicles, the greater the $RFE_{i,f(j)}$ becomes. This describes the situation where more agents using electric vehicles leads to an increase in the number of charging stations. Therefore, the assumption of the refueling effect allows us to at least partially account for infrastructure progress.

4.3. Setting susceptibilities and driving patters

We estimate values of susceptibilities and driving patterns based on survey responses which were also used for the conjoint analysis [51]. In the survey, respondents were asked how much different sources of information influence their opinions on HEVs, PHEVs, and BEVs. The responses were reported in a 5-level scale from 0 (no influence) to 4 (great influence). We relate susceptibilities to marketing, $p^{\text{adv}}_{i,f(j)}$, local influence, $p^{\text{local}}_{i,f(j)}$, and global influence, $p^{\text{global}}_{i,f(j)}$, with responses to the questions about the following sources of information: "I have seen, read, or heard about this car type in media", "I have talked with the owner of this car type", and "I have seen this car type on the street", respectively. Figure 2 presents the frequency histograms of collected responses, whereas Table 2 includes the related summary statistics. As seen, direct recommendation from the car owner (i.e., local influence) is considered the most influential.

In the same survey, respondents reported how many kilometers they plan to drive with a car on average per year. Figure 3 presents a box-plot [21] displaying the reported data. The box is drawn from the 1st quartile (Q1) to the 3rd quartile (Q3), and the horizontal line inside the box denotes the median. The whiskers are drawn based on the 1.5IQR value, where IQR is the interquartile range, i.e., IQR $=$ Q3 $-$ Q1. Up from Q3, a distance of 1.5IQR is measured out, and the upper whisker extends to the largest observation that lies within this distance. Similarly, a distance of 1.5IQR is measured down from Q1, and the lower whisker extends to the smallest observation that falls within this distance. All data outside the whiskers are considered outliers [21]; see the red cross marks in Figure 3(a). In our case, there are 47 responses that are classified as outliers since they lie above the limit of the upper whisker, which is 60 000 km. The summary statistics related to this data is presented in Table 3.

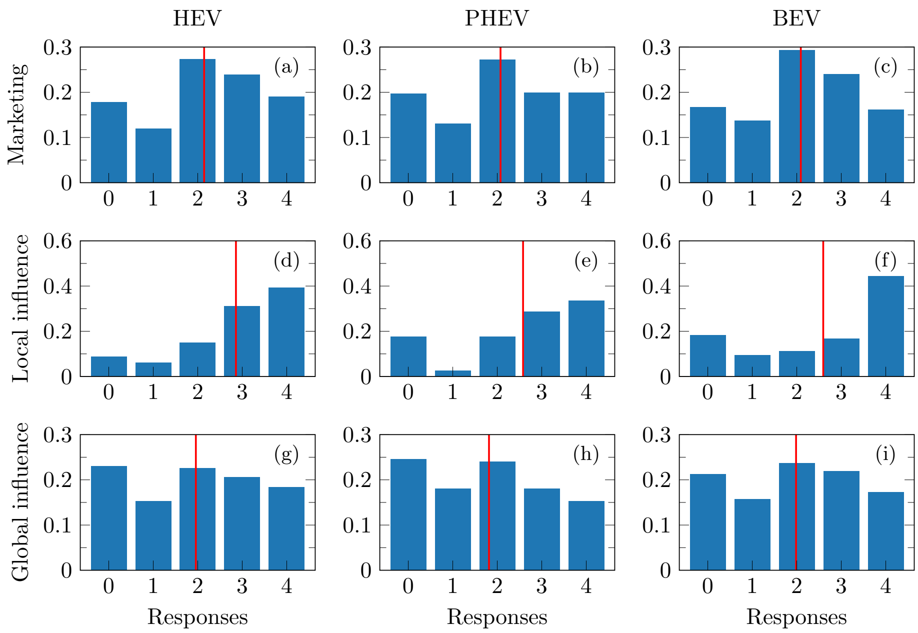

Figure 2. Frequency histograms of the servery responses to the question of how many different sources of information (i.e., marketing, local influence, and global influence) impact the opinions of HEVs, PHEVs, and BEVs. The answers were reported in 5-level scale from 0 (no influence) to 4 (great influence). Vertical, red lines indicate the mean values. The related summary statistics are presented in Table 2.

Table 2. Summary statistics for the susceptibilities associated with different vehicle types

	HEV			PHEV			BEV		
	Mean	SD	N	Mean	SD	N	Mean	SD	N
Marketing	2.14	1.35	641	2.07	1.38	451	2.09	1.30	650
Local influence	2.86	1.25	283	2.58	1.43	119	2.59	1.56	180
Global influence	1.96	1.42	593	1.81	1.39	366	1.98	1.39	560

The summary includes the mean, the standard deviation (SD), and the number of cases (N).

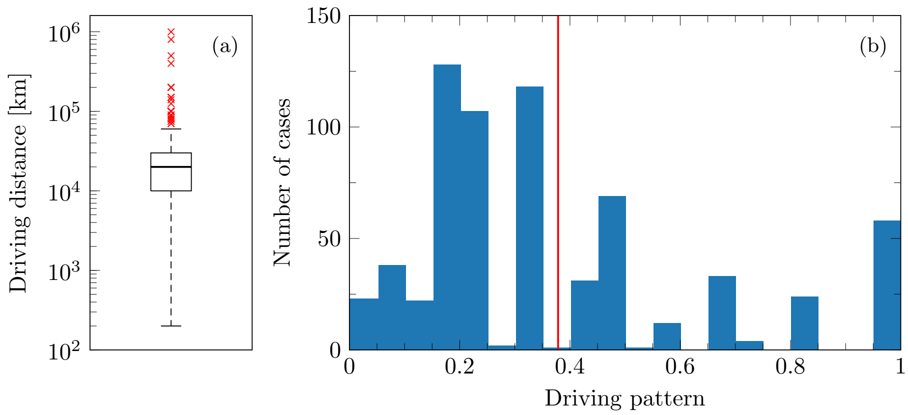

Figure 3. Boxplot of the yearly average driving distances reported in the survey (a) and the histogram of driving patterns used in the simulations (b).
In panel (a), red cross marks indicate the outliers. In panel (b), the vertical, red line indicates the mean value. The related summary statistics are presented in Table 3

To obtain the distribution of driving patterns, we have to transform all the responses into a range from 0 (short trips) to 1 (distant journeys) (Section 4.2). In [74], based on the observation that the yearly average driving distance in Germany follows a positively skewed distribution, a lognormal distribution with mean

-0.85 and standard deviation 0.65 of the underlying normal distribution was chosen for driving patterns with the restriction that the values obtained do not exceed 1.

Table 3. Summary statistics for the average annual driving distance reported in the survey and the driving pattern obtained

	Min	Q1	Median	Mean	Q3	Max	SD	N
Driving distance, km	200	10,000	20,000	29 638	30,000	999,000	59 779	671
Driving pattern	0.003	0.167	0.333	0.378	0.500	1.000	0.265	

The summary includes the minimum value (Min), the 1st quartile (Q1), the median, the mean, the 3rd quartile (Q3), the maximum value (Max), the standard deviation (SD), and the number of cases (N).

However, the exact estimation procedure is not reported. Later works used different scaling strategies to adapt the German driving pattern to other countries such as Iceland [76] or the USA [60, 75]. Some studies use only one driving pattern for all agents and system replications [41, 76], others randomly select it in each system replication [60, 75]. Not having found an objective and well-described procedure to transform yearly average driving distances to driving patterns, we propose a non-parametric procedure based on a box plot. In our method, all outliers above the upper whisker are considered distant journeys, and they are transformed into driving patterns of value 1. The rest of the reported yearly average driving distances are divided by the limit of the upper whisker, which is 60,000 km in our case. The resulting distribution of driving patterns is presented in Figure 3. By this procedure, we get the average driving pattern for Poland of around 0.38. For comparison, the average driving pattern is estimated to be 0.49 for Germany [74], 0.78 for Iceland [76], and 0.60 for the USA [60, 75].

We use either heterogeneous or homogeneous conditions to initialize the susceptibilities and driving patterns. In the heterogeneous case, given parameters of agents are drawn randomly from the corresponding empirical distributions, which are presented in Figs. 2 and 3(b). In this scenario, the agents have characteristic personal traits and differ from each other. On the other hand, the homogeneous conditions imply that given agents' parameters take the mean values of the corresponding empirical distributions. These means are depicted as vertical red lines in Figs. 2 and 3(b). In this case, all agents have the same values of the parameters. We consider four different combinations of initialization conditions since the susceptibilities and driving patterns can be initialized independently in a heterogeneous or homogeneous way.

4.4. Simulation code and algorithm

We implemented the model in C++ with the support of the object-oriented programming paradigm. Python was used to run the simulations, calibrate the model, and analyze the data. The codes for this project are maintained on GitHub. The release of the software used for this publication is archived on Zenodo under the following links:

- arkadiusz-jedrzejewski/alternative-fuel-vehicle-abm,
- arkadiusz-jedrzejewski/alternative-fuel-vehicle-abm-py.

Each Zenodo archive includes a link to the corresponding repository on GitHub, where you can find the latest version of the software. The algorithm to simulate our model is presented below, see also a flowchart in Figure 4.

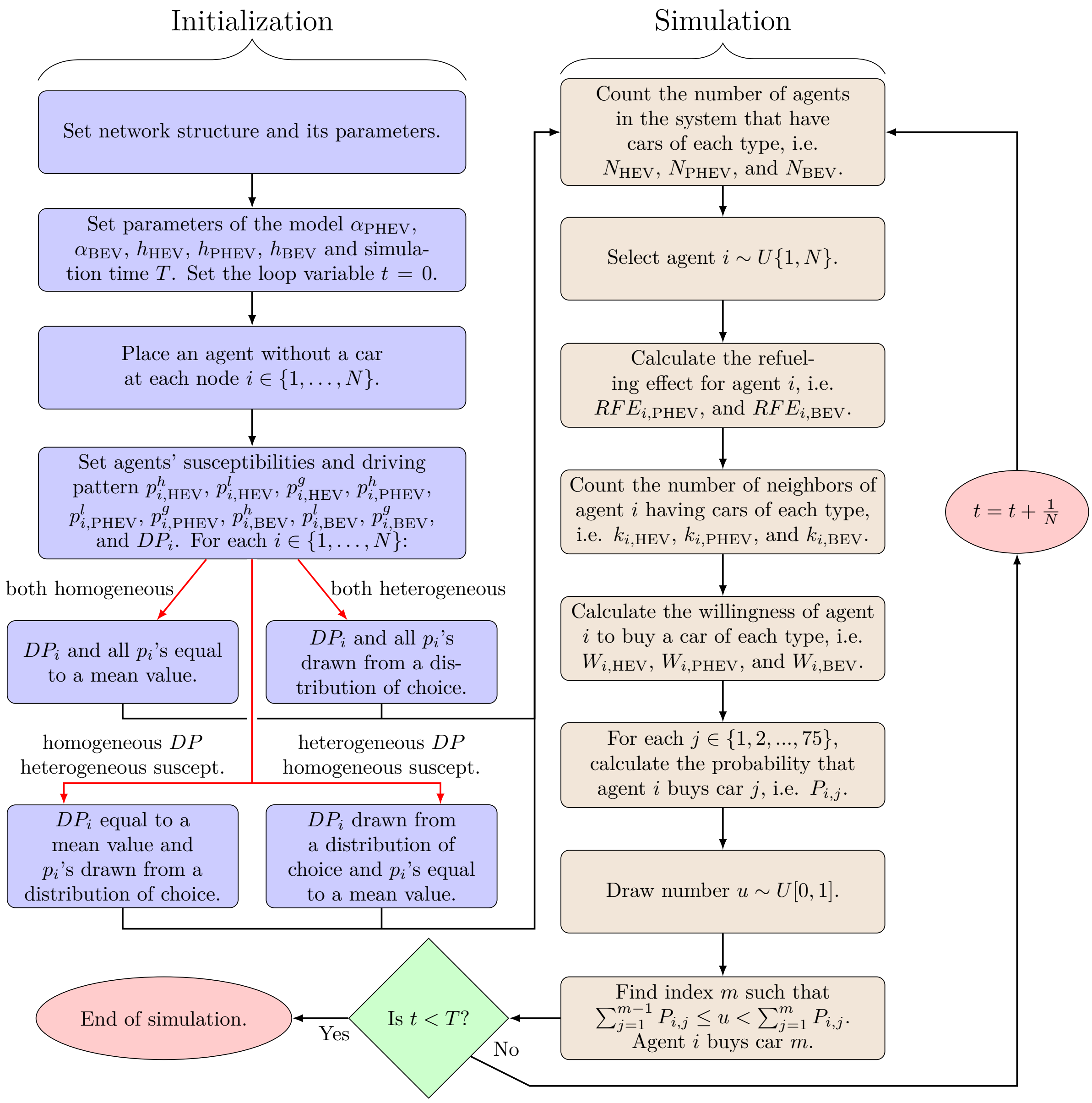

Figure 4. Flowchart of the simulation algorithm. The crucial part of the initialization phase, i.e., the choice between homogeneity and heterogeneity of both driving patterns and susceptibilities, is marked with red arrows.

The procedure for initializing the system is as follows:

1. Choose the network structure and the relevant network parameters, e.g., the number of nodes in the network, N.
2. Set other model parameters: α_{PHEV}, α_{BEV}, h_{HEV}, h_{PHEV}, h_{BEV}, and the time horizon of the simulation, T.
3. Place an agent without a car at each node $i \in \{1, \dots, N\}$ of the network.
4. Assign susceptibilities and driving patterns to agents. For each agent $i \in \{1, \dots, N\}$, choose the values of:
   - the susceptibilities related to hybrid electric vehicles: $p^{\text{adv}}_{i,\text{HEV}}$, $p^{\text{local}}_{i,\text{HEV}}$, $p^{\text{global}}_{i,\text{HEV}}$,
   - the susceptibilities related to plug-in hybrid electric vehicles: $p^{\text{adv}}_{i,\text{PHEV}}$, $p^{\text{local}}_{i,\text{PHEV}}$, $p^{\text{global}}_{i,\text{PHEV}}$,
   - the susceptibilities related to battery electric vehicles: $p^{\text{adv}}_{i,\text{BEV}}$, $p^{\text{local}}_{i,\text{BEV}}$, $p^{\text{global}}_{i,\text{BEV}}$,
   - and the driving pattern: DP_i.

If heterogeneous conditions are used, randomly draw these values from the corresponding empirical distributions (Figures 2 and 3(b)). If homogeneous conditions are used, set these values to the corresponding means of susceptibilities and driving patterns from Tables 2 and 3.

After the system is initialized, the simulation is performed in the following way.

1. Count the number of agents in the system that have cars of each type, i.e., N_{HEV}, N_{PHEV}, and N_{BEV}.
2. Draw the number i from the discrete uniform distribution $U\{1, N\}$. The agent i is selected to buy a car.
3. Calculate the refueling effect for agent i from equation (5) for PHEVs and BEVs, i.e., $RFE_{i,\text{PHEV}}$ and $RFE_{i,\text{BEV}}$.
4. Count the number of neighbors of agent i that have cars of each type, that is, $k_{i,\text{HEV}}$, $k_{i,\text{PHEV}}$, and $k_{i,\text{BEV}}$.
5. Calculate the willingness of agent i to buy a car of each type from equation (4), i.e., $W_{i,\text{HEV}}$, $W_{i,\text{PHEV}}$, and $W_{i,\text{BEV}}$.
6. For each $j \in \{1, 2, \ldots, 75\}$, calculate the probability that agent i buys a car j, i.e., $P_{i,j}$ from equation (2).
7. Draw the number u from the uniform continuous distribution $U[0, 1]$.
8. Find an index m such that $\sum_{j=1}^{m-1} P_{i,j} \leq u < \sum_{j=1}^{m} P_{i,j}$. Agent i buys car m.
9. Update time $t \to t + 1/N$. If $t < T$, go to point 1.

The time in our simulations is measured in Monte Carlo steps (MCS). In one Monte Carlo step, N agents are randomly selected to purchase a car. The agents are chosen with repetition.

4.5. Model calibration procedures

We use the tree-structured Parzen estimator algorithm implemented in Hyperopt Python library to calibrate the model. The tree-structured Parzen estimator algorithm is a Bayesian optimization method, which can more efficiently explore the parameter space compared to the simple grid-search method [8]. This algorithm iteratively searches for the optimal parameters by creating a probabilistic model based on the history of evaluated parameters. The model is then used to select next set of parameters to evaluate. We define the parameter search space as $\alpha_{\text{PHEV}} \in [0, 14]$, $\alpha_{\text{BEV}} \in [0, 1.5]$, and $h_{\text{HEV}}, h_{\text{PHEV}}, h_{\text{BEV}} \in [0, 4]$. These regions of the parameter search space were chosen based on an initial rough grid search calibration presented in Appendix B.

The loss function is the mean square error (MSE) between the adoption levels estimated in the survey and the stationary adoption levels obtained from 500 independent simulations:

$$\text{MSE} = \frac{1}{500} \sum_{i=1}^{500} \frac{1}{3} \left[\left(x^*_{\text{HEV}} - x^{\text{st}}_{\text{HEV},i} \right)^2 + \left(x^*_{\text{PHEV}} - x^{\text{st}}_{\text{PHEV},i} \right)^2 + \left(x^*_{\text{BEV}} - x^{\text{st}}_{\text{BEV},i} \right)^2 \right] \tag{6}$$

where x^*_{HEV}, x^*_{PHEV}, and x^*_{BEV} are the adoption levels estimated in the survey and $x^{\text{st}}_{\text{HEV},i}$, $x^{\text{st}}_{\text{PHEV},i}$, and $x^{\text{st}}_{\text{BEV},i}$ are the stationary adoption levels in the ith simulation.

According to the survey data presented in Table 8 in [51], around 48.9% of the respondents would buy a HEV, 31.9% a PHEV, and 19.2% a BEV. Thus, we set $x^*_{\text{HEV}} = 0.489$, $x^*_{\text{PHEV}} = 0.319$, and $x^*_{\text{BEV}} = 0.192$ in equation (6). Figure 5 illustrates these results in the form of a pie chart. Keep in mind that consumers may react differently to hypothetical questionnaires and real market choices [11]. Thus, the survey results correspond only to hypothetical purchases, not to actual market shares.

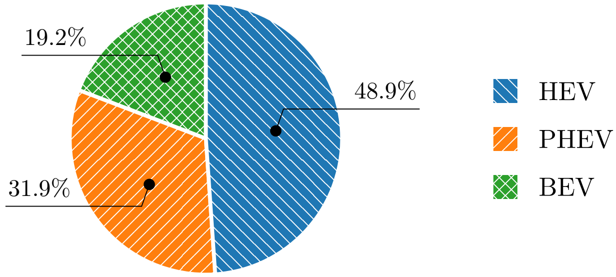

Figure 5. Pie chart showing the percentage of respondents who would hypothetically purchase an alternative fuel vehicle in a given category. The chart is plotted based on the data taken from Table 8 in [51]. This data is used to calibrate the model

Table 4. Parameters α_{PHEV}, α_{BEV}, h_{HEV}, h_{PHEV}, and h_{BEV} obtained from the calibration procedure based on the tree-structured Parzen estimator algorithm for different model setups with the corresponding mean square error (MSE)

Heterogeneous Susceptibilities	Heterogeneous Driving patterns	α_{PHEV}	α_{BEV}	h_{HEV}	h_{PHEV}	h_{BEV}	MSE
Square lattice with $N = 1024$ agents (32×32)							
No	no	1.749	0.753	3.718	3.664	2.063	0.000248
No	yes	11.076	0.513	3.827	2.785	2.330	0.000241
Yes	no	8.363	1.312	3.355	2.310	1.514	0.000271
Yes	yes	7.951	0.032	3.845	2.707	2.331	0.000246
Watts–Strogatz network with $N = 1024$ agents. $\langle k \rangle = 4$. and $\beta = 0$							
No	no	10.328	1.176	3.711	2.635	1.946	0.000249
No	yes	8.180	1.028	3.515	2.628	2.063	0.000255
Yes	no	7.337	0.543	3.856	2.717	1.962	0.000248
Yes	yes	7.391	1.077	3.999	2.873	2.030	0.000271
Watts–Strogatz network with $N = 1024$ agents. $\langle k \rangle = 4$. and $\beta = 1$							
No	no	9.156	0.834	3.736	2.682	2.088	0.000240
No	yes	12.170	0.165	3.740	2.711	2.484	0.000240
Yes	no	3.566	1.200	3.837	3.072	1.751	0.000269
Yes	yes	10.465	0.858	3.675	2.539	1.903	0.000267

The calibration of the model is performed separately for each simulation setting. First, we choose the network (Section 4.1) and assign susceptibilities and driving patterns to agents using heterogeneous or homogeneous conditions (Section 4.3). Next, we perform the calibration process – calibrated parameters, α_{PHEV}, α_{BEV}, h_{HEV}, h_{PHEV}, and h_{BEV} are those that minimize the mean square error (Table 4). To obtain the dependence between the model parameters and the adoption levels, we use the warm-up period prior to data collection, in line with good simulation practice, see for example [70]. As shown in Figure 6, the adoption levels settle down very quickly, so we choose a warm-up period of 20 MCS, which is more than enough. All statistical measures are calculated based on the ensemble of 500 independent simulations.

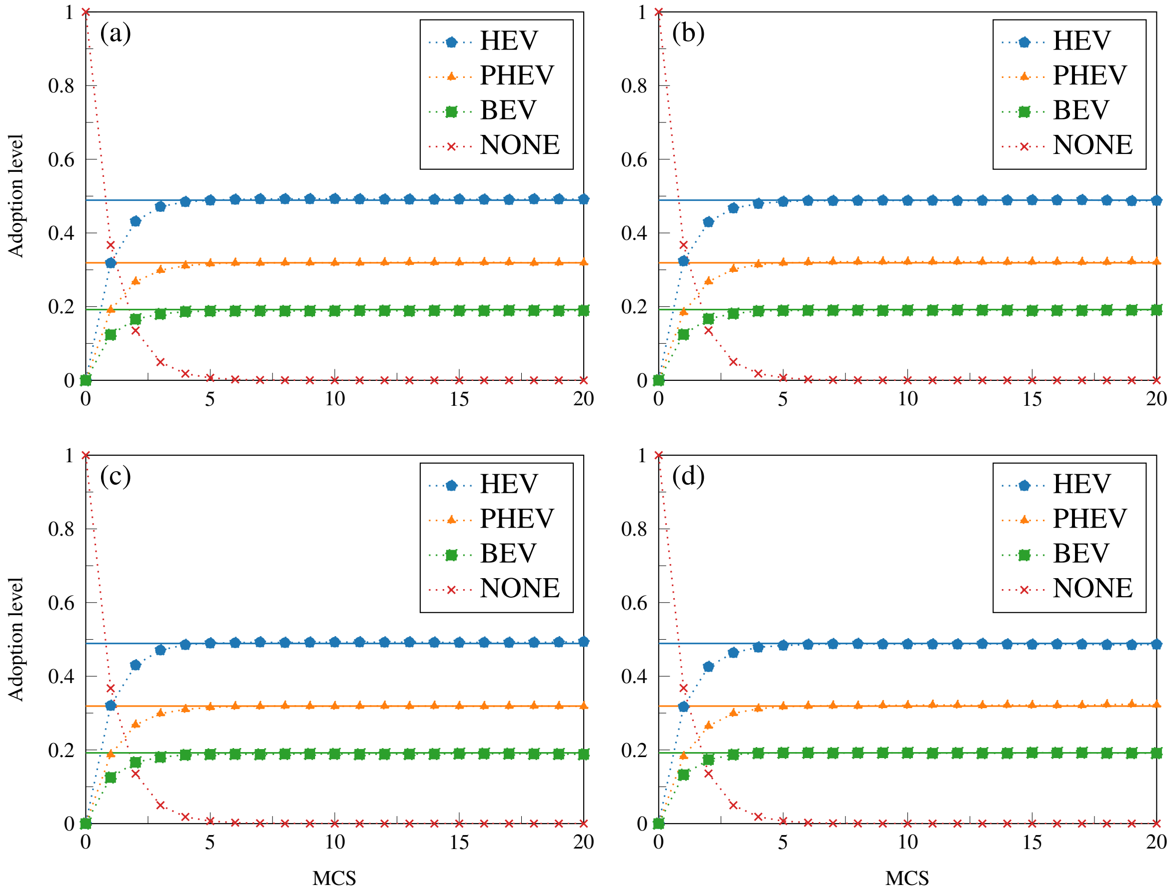

Figure 6. Time evolution of the adoption levels of AFVs for the models on a square lattice of $N = 1024$ agents (32×32) for optimal values of α_{PHEV}, α_{BEV}, h_{HEV}, h_{PHEV}, and h_{BEV} (Table 4), obtained for different combinations of heterogeneous and homogeneous conditions: a) homogeneous susceptibilities and driving patterns, b) homogeneous susceptibilities and heterogeneous driving patterns, c) heterogeneous susceptibilities and homogeneous driving patterns, and d) heterogeneous susceptibilities and driving patterns. Symbols represent the average (mean) trajectory, and the error bars, representing the standard error of the mean (SEM), are of the order of the symbol size. Horizontal, continuous lines correspond to the percentages estimated in the survey [51]; Figure 5. NONE represents the fraction of agents without a car.

5. Results

We study our model on 3 networks with the same number of agents, $N = 1024$, and the average degree, $\langle k \rangle = 4$: a square lattice (32×32 agents), Watts–Strogatz network with $\beta = 0$, and Watts–Strogatz network with $\beta = 1$ (Section 4.1).

It can be argued that the parameters we have chosen are not very realistic, for example $\beta = 0$ and $\beta = 1$ do not reflect the properties of real social networks. We agree with this potential criticism – it would be more realistic to consider $\beta \in (0.01, 0.1)$ [89]. However, we wanted to see if the network structure mattered at all for our model, so we chose the extreme values of β. It turned out that the network structure does not really affect the results. One may also wonder why we use such a small system, i.e., $N = 1024$. This size was dictated by the number of people who participated in the empirical studies described in Ref. [51] from which we took the empirical data to calibrate the model.

We consider 4 different combinations of initialization conditions: the susceptibilities and the driving patterns can be initialized independently in a heterogeneous or homogeneous way (Section 4.3). With four initialization conditions and three different network structures, we analyze a total of 12 models.

5.1. Results of the model calibration

We calibrate parameters for all considered models, as seen in Table 4. α_{BEV} is around one order of magnitude smaller than α_{PHEV} in most of the cases. Interestingly, a completely different calibration procedure, so-called grid-search calibration, gives qualitatively the same result (Appendix B), which suggests that the refueling effect could have a greater impact on the diffusion of BEVs. This is consistent with the literature, which identifies the limiting cruising range as a major barrier to the widespread adoption of electric vehicles [47].

The second outcome from the calibration is that for all the models, $h_{\mathrm{HEV}} > h_{\mathrm{PHEV}} > h_{\mathrm{BEV}}$, which means that HEVs are advertised the most, whereas BEVs are advertised the least. Assessing the realism of this result is challenging. HEVs, which have been on the market longer than PHEVs and BEVs, are more familiar to consumers and may have received more advertising in the past. Unfortunately, we were unable to find rigorous data to confirm this. However, some recent marketing reports [4, 27, 38] suggest that this result may be accurate, which will be discussed in the conclusions.

Considering the calibration results presented in Figure 6, we included this figure mainly to show that all models can be calibrated and behave very similarly and that the warm-up time needed to reach stabilized values is short. We did not want to draw any deep conclusions about the temporal behavior of the system, since we did not define how to scale our simulation time to the real one. However, it is reasonable to make at least one suggestion regarding the temporal behavior adopted. According to Rogers' theory [71], one might expect the s-shaped curve which is not observed in Figure 6. Traditionally, diffusion curves (i.e., plots of the number of individuals observed to have performed a particular behavior versus time) have been assumed to be s-shaped in the case of social learning and r-shaped (as in Figure 6) in the case of asocial learning [36]. Therefore, our results could indicate that asocial learning dominates in AFV adoption. This finding is surprisingly consistent with the results on the role of marketing presented in the next section.

5.2. The role of the marketing

After calibrating the model, we examine how the strength of marketing affects the steady-state adoption levels of different AFVs. We compare models calibrated to different networks and various combinations of heterogeneous and homogeneous initial conditions. Each panel of Figs. 7–9 illustrates the results for the systems where we vary the marketing strength for only one vehicle category, and the rest of the marketing strengths are set to the calibrated values presented in Table 4. These figures consist of 9 panels arranged in 3 columns and 3 rows: each column corresponds to a different network structure and each row corresponds to a different vehicle category.

As expected, when only HEVs are advertised more, see the results in Figure 7, adoption increases for HEVs while it decreases for the other two vehicle categories. Unexpectedly, the type of network and the method used to initialize driving patterns do not significantly affect the results. Similar results are obtained when only PHEVs (Figure 8) or BEVs (Figure 9) are advertised more. In all three cases, the largest differences between the models are seen on the square lattice, which corresponds to the left columns of Figs. 7–9. These differences are rather small, but still we find this result interesting because the square lattice best reflects the physical space of all the network structures we considered. Taking physical space into account seems to be important, as a study by Generation180 from 2023 showed that people are more likely to drive electric vehicles if their neighbors also drive them [28]

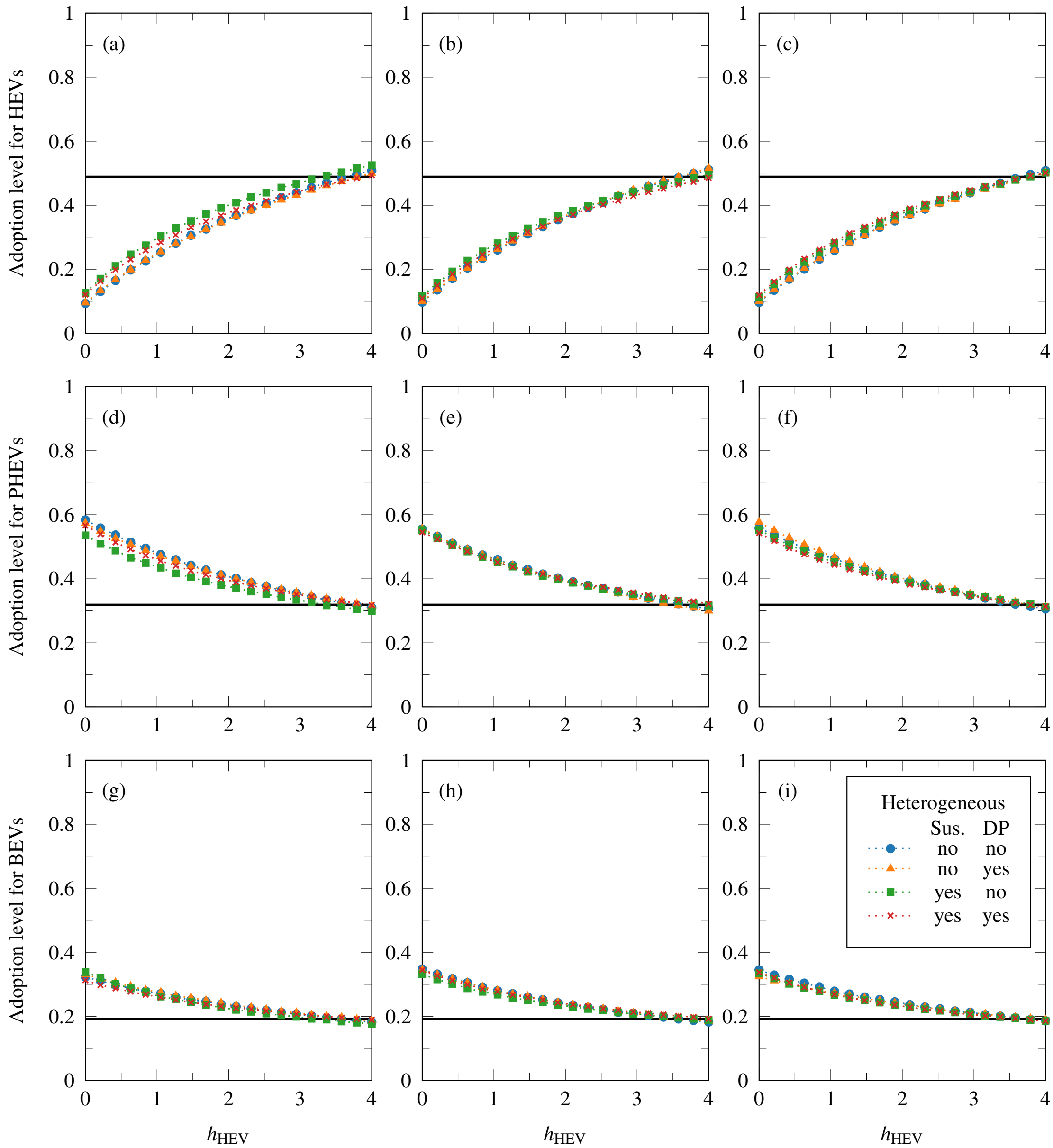

Figure 7. Dependence between the stationary adoption levels and the marketing strength of HEV. Each column corresponds to a different network structure and each row corresponds to a different vehicle category: (a)–(c) HEVs, (d)–(f) PHEVs, and (g)–(i) BEVs obtained for the models with different combinations of initialization conditions. Networks: left column – square lattice with $N = 1024$ agents (32×32); middle column – Watts–Strogatz network with $N = 1024$ agents, $\langle k \rangle = 4$, and $\beta = 0$; right column – Watts–Strogatz network with $N = 1024$ agents, $\langle k \rangle = 4$, and $\beta = 1$. Only the marketing strength for HEVs is varied, the rest of the marketing strengths are set to the calibrated values (Table 4). Horizontal continuous lines correspond to the percentages estimated in the survey [51]; see Figure 5. The error (SEM) bars are of the order of the symbol size

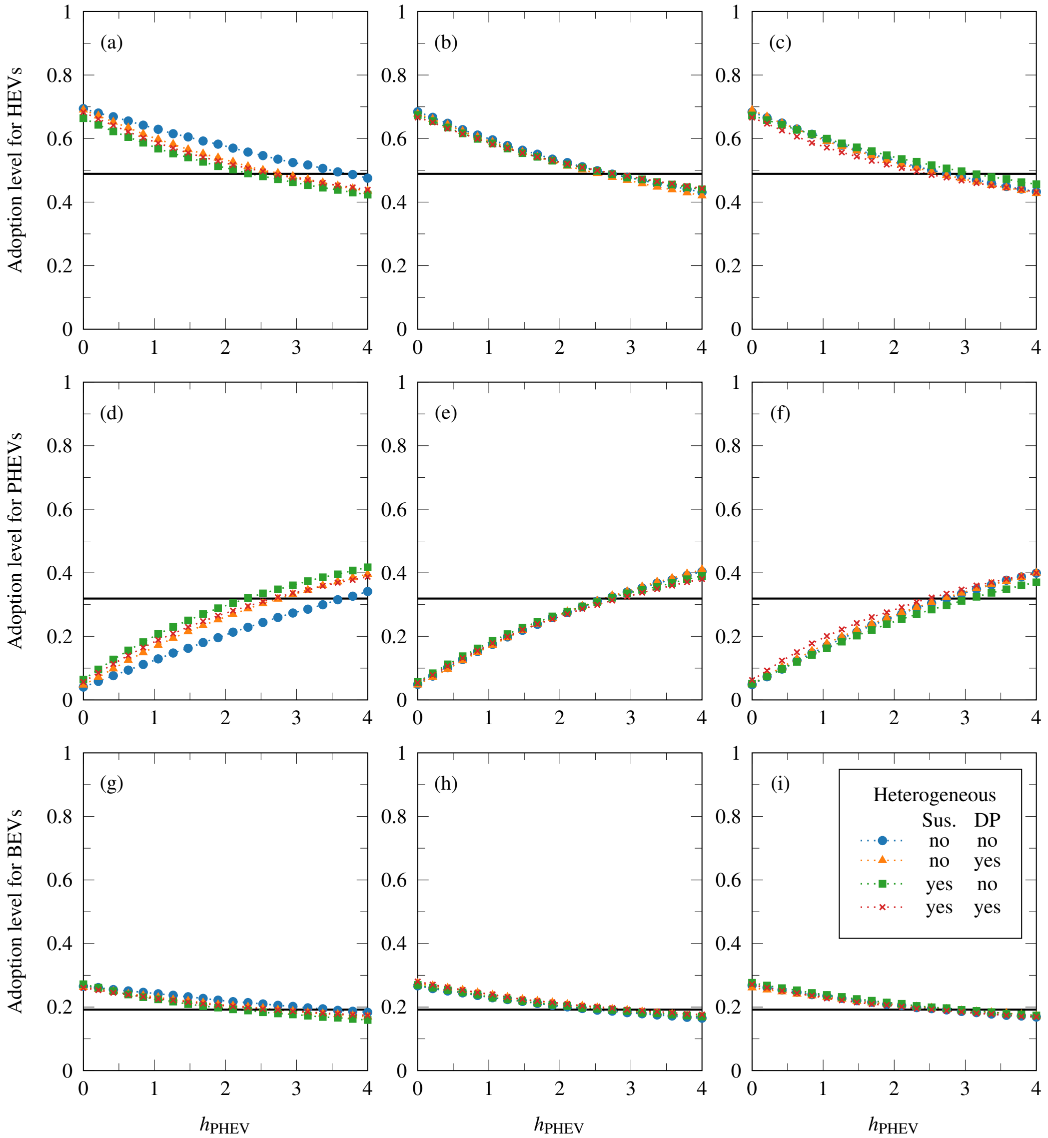

Figure 8. Dependence between the stationary adoption levels and the marketing strength of PHEV. Each column corresponds to a different network structure and each row corresponds to a different vehicle category: (a)–(c) HEVs, (d)–(f) PHEVs, and (g)–(i) BEVs obtained for the models with different combinations of initialization conditions. Networks: left column – square lattice with $N = 1024$ agents (32×32); middle column – Watts–Strogatz network with $N = 1024$ agents, $\langle k \rangle = 4$, and $\beta = 0$; right column – Watts–Strogatz network with $N = 1024$ agents, $\langle k \rangle = 4$, and $\beta = 1$. Only the marketing strength for PHEVs is varied, the rest of the marketing strengths are set to the calibrated values (Table 4). Horizontal, continuous lines correspond to the percentages estimated in the survey [51] (Figure 5). The error (SEM) bars are of the order of the symbol size

Although we observe some differences between the models on the square lattice, these differences are very small. What has by far the greatest impact on the level of adoption is the strength of marketing. This is also consistent with our discussion on asocial learning – marketing seems to be more important than peer pressure in this case. We find this result particularly interesting in light of recent market trends. In 2023, Ireland significantly reduced subsidies for PHEVs, and Germany eliminated them. Soon, in 2024, for the first time since 2018, there is a decline in electric car sales in Europe [38]. We do not claim that the reduction of subsidies was the only reason for this decline, but it was probably one of the main reasons.

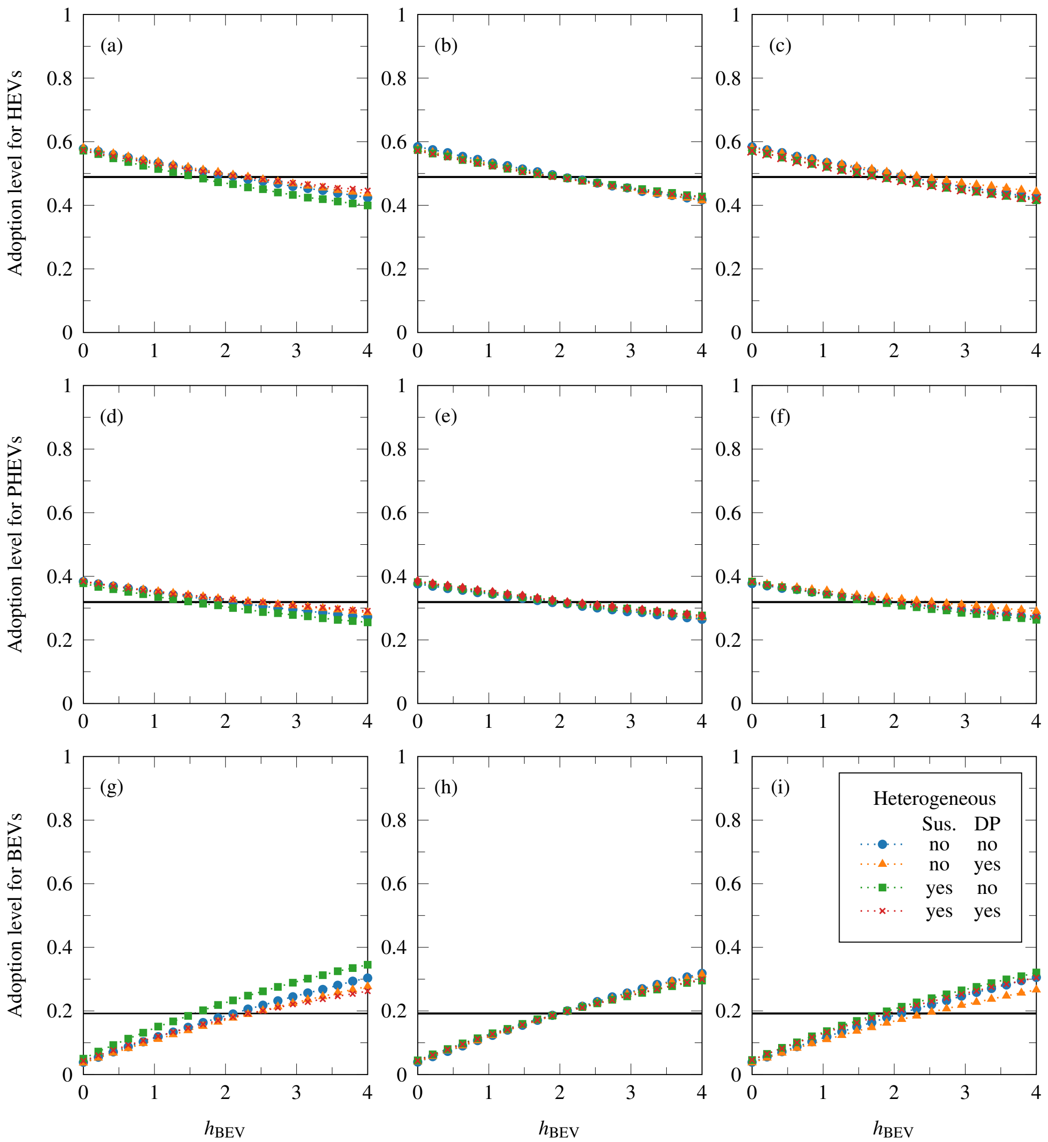

Figure 9. Dependence between the stationary adoption levels and the marketing strength of BEV. Each column corresponds to a different network structure and each row corresponds to a different vehicle category: (a)–(c) HEVs, (d)–(f) PHEVs, and (g)–(i) BEVs obtained for the models with different combinations of initialization conditions. Networks: (left column) square lattice with $N = 1024$ agents (32×32); middle column – Watts–Strogatz network with $N = 1024$ agents, $\langle k \rangle = 4$, and $\beta = 0$; right column – Watts–Strogatz network with $N = 1024$ agents, $\langle k \rangle = 4$, and $\beta = 1$. Only the marketing strength for BEVs is varied, the rest of the marketing strengths are set to the calibrated values (Table 4). Horizontal, continuous lines correspond to the percentages estimated in the survey [51] (Figure 5). The error (SEM) bars are of the order of the symbol size

6. Conclusions

According to the International Energy Agency's (IEA's) Global EV Outlook 2024, electric vehicle registrations and sales grew monotonically from 2018 to 2023 [38]. However, already in 2023 this growth slowed down significantly in Europe and even declined in 2024: the share of battery electric cars decreased from 13.9% in 2023 to 13% in 2024, while the share of hybrid electric cars increased from 24.4% to 29% [27]. Was this expected? On the contrary, most forecasts, including those from reputable sources such as the IEA, typically predict continued growth, especially for BEVs. So what could be the reason? There could be many, including a reduction in government incentives, a shift in consumer preferences, etc. For example, Germany has decided to end subsidies for PHEVs in 2023 [38]. In addition, according to the AlixPartners 2024 International Electric Vehicle Consumer-Sentiment Survey, concerns about charging infrastructure and range are causing BEV intenders in the U.S. and Europe to shift their interest to PHEVs [4]. The survey also notes that while BEV loyalty has increased, BEV intentions among consumers of traditional (internal combustion engine) vehicles have stagnated, suggesting a near-term preference shift toward hybrids as an alternative to BEVs. This is particularly striking in light of our findings, which we summarize below.

First, our calibration showed that the $\alpha_{\mathrm{BEV}} < \alpha_{\mathrm{PHEV}}$, meaning that the refueling effect could have a greater impact on BEV penetration. This result was robust and repeated within both calibration methods, across all 12 models we analyzed (Tables 4 and B1). This result validates the model, as limited driving range has been identified as a major barrier to the widespread adoption of electric vehicles [47].

The second result of the calibration is that the marketing strength for HEVs, given by h_{HEV}, is the largest among all alternative fuel vehicles. This result was also very robust and repeated across all 12 models we analyzed. Although not very surprising, given that we calibrated the model to the empirical data showing HEVs to be the most popular, it is still interesting when compared to recent market trends, described above, and serves as a second validation of our model.

Third, we show that heterogeneity in individual consumer characteristics (susceptibilities and driving patterns) plays a minor role compared to marketing strength. At this point, we would like to emphasize that in our model, marketing strength describes all factors that are global, i.e., that affect all agents, and does not depend on the number of adopted agents, so in fact it may represent asocial learning. This means that marketing strength can describe subsidies, advertising, awareness campaigns, etc. This shows the importance of government incentives, which is also confirmed by recent market trends showing the decline in AFV sales after the reduction of subsidies. Although we are not sure whether the reduction of subsidies actually led to a decrease in the number of electric cars purchased, it seems to be one of the important reasons.

Fourth, although heterogeneity in individual consumer characteristics does not significantly affect the results in any of the networks considered, it definitely affects the results the most in the square lattice. This result is also interesting given that the square lattice may be the most appropriate to study the diffusion of AFVs because it reflects physical space. This seems important given that people are more likely to drive electric vehicles if their neighbors do [28].

All of the above results validate our model. However, creating a realistic model with predictive power was not the primary goal of this work. As mentioned in the introduction, the main goal was to test how different heterogeneities affect the macroscopic behavior of the system. We considered heterogeneity related to the personal characteristics of the agents (susceptibilities and driving patterns) and network heterogeneity, which is more subtle and will be discussed later. Consequently, we analyzed 12 versions of the model: four combinations of heterogeneity in terms of susceptibilities and driving patterns across three types of networks.

We start the discussion with the heterogeneity related to the personal characteristics of the agents. In the heterogeneous conditions, the susceptibilities and driving patterns of the agents were randomly drawn from the corresponding empirical distributions shown in Figs. 2 and 3. In the homogeneous conditions, all agents had the same values of susceptibilities and driving patterns, which is an expected value from the same empirical distributions. This means that the expected value of the susceptibilities and driving patterns were the same in the heterogeneous and homogeneous conditions.

We were able to calibrate all of these models to the macroscopic empirical data on the percentage of respondents who would hypothetically purchase an alternative fuel vehicle of a given category, shown in Figure 5. Moreover, all of these calibrations produced qualitatively similar results, as discussed above, although the specific values of the calibrated parameters were slightly different. Since we do not know what the real values of these parameters are, we cannot evaluate which of the models is the most appropriate. Moreover, qualitatively, all the models gave almost identical results. Of course, this result is not universal – heterogeneity can play an important role [6]. In one of our previous papers, we showed that whether heterogeneity is needed depends on the model itself and on the network on which it is considered – in some cases, homogeneous and heterogeneous features of agents can lead to the same result at the macroscopic scale, but sometimes they are significantly different [40].

A similar result we observed in our model – as long as we consider the model on WS network, heterogeneity of individual preferences is not needed in the sense that including heterogeneity does not influence results on the macroscopic level. However, they start to become more important, although not very important on the square lattice. And so we reach the issue of heterogeneity related to the structure of the network. At first glance, the square lattice appears to be as regular as possible. It is true that in such a network, each agent has the same degree, i.e., the same number of nearest neighbors (separation degree 1), next nearest neighbors (separation degree 2), and so on. Moreover, the distance in physical space is the same for all neighbors with a given degree of separation. However, it is in such a network that the strongest spatial heterogeneity in consumer preferences appears, which is caused by local interactions with neighbors. In some areas the concentration of adopters is low and in others, it is high [85]. This behavior is also observed empirically in real systems [28].

In summary, there are two main messages that we want the reader to take away. The first is that what appears homogeneous at first glance may not be so in ABM. Interactions between agents can produce spatial heterogeneity that would not exist without those interactions, and the square lattice is a very good example of such “hidden” heterogeneity. The second and main message of this paper is that although real social systems are heterogeneous in many ways, not all heterogeneity affects the outcome at the macroscopic level. Therefore, it is always worth verifying if heterogeneity has an impact on the model performance and in case it does not, rely on the simpler, homogeneous simulation setup. To our mind, it does not make se nse to complicate the model unless it allows us to observe some additional aspects of the examined system.

Acknowledgement

This work was supported by the National Science Center (NCN, Poland) by grants Nos. 2018/29/B/HS4/00069 and 2019/35 /B/HS6/02530. Arkadiusz Jędrzejewski is EUTOPIA-SIF COFUND Marie Skłodowska-Curie Fellow at CY Cergy Paris Université, CY Advanced Studies, Neuville-sur-Oise, 95000, France.

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Appendices

A. Car attributes and partial utilities

In this Appendix, we present the following data previously shown in Ref. [51]: profiles of 25 HEVs in Table A1, PHEVs in Table A2 and BEVs in Table A3, as well as attributes of vehicles together with their corresponding partial utilities in Table A4. We provide them here for convenience and to facilitate understanding of the model.

Table A1. Profiles of 25 HEVs considered in the simulations

ID	Safety level	Purchase price [PLN]	Access to service [km]	Functionality level	Car type
1	low	150,000	130	low	Urban
2	very high	300,000	40	very high	Urban
3	medium	250,000	130	very low	Compact
4	very high	150,000	100	very low	Sedan
5	very low	300,000	130	medium	VAN
6	very high	200,000	130	high	SUV
7	low	100,000	100	high	VAN
8	medium	150,000	70	very high	VAN
9	medium	100,000	40	low	SUV
10	very low	100,000	10	very low	Urban
11	high	100,000	130	very high	Sedan
12	high	150,000	10	medium	SUV
13	low	300,000	70	very low	SUV
14	very low	250,000	100	very high	SUV
15	very high	100,000	70	medium	Compact
16	medium	200,000	100	medium	Urban
17	high	250,000	70	high	Urban
18	very low	200,000	70	low	Sedan
19	medium	300,000	10	high	Sedan
20	very low	150,000	40	high	Compact
21	low	250,000	40	medium	Sedan
22	high	200,000	40	very low	VAN
23	low	200,000	10	very high	Compact
24	very high	250,000	10	low	VAN
25	high	300,000	100	low	Compact

The same car profiles were used in the conjoint analysis in Ref. [51].

Table A2. Profiles of 25 PHEVs considered in the simulations

ID	Safety level	Purchase price [PLN]	Access to service [km]	Functionality level	Car type
1	medium	300,000	70	40	60
2	very high	150,000	70	100	20
3	very high	250,000	130	70	100
4	very low	150,000	40	70	60
5	low	200,000	40	100	40
6	medium	250,000	40	130	20
7	medium	200,000	10	70	80
8	very high	200,000	100	10	60
9	low	300,000	100	70	20
10	low	250,000	70	10	80
11	low	100,000	130	130	60
12	medium	150,000	130	10	40
13	very high	300,000	10	130	40
14	high	300,000	40	10	100
15	medium	100,000	100	100	100
16	high	100,000	70	70	40
17	very low	100,000	10	10	20
18	very high	100,000	40	40	80
19	very low	250,000	100	40	40
20	high	200,000	130	40	20
21	high	150,000	100	130	80
22	high	250,000	10	100	60
23	very low	300,000	130	100	80
24	very low	200,000	70	130	100
25	low	150,000	10	40	100

The same car profiles were used in the conjoint analysis in Ref. [51].

Table A3. Profiles of 25 BEVs considered in the simulations

ID	Safety level	Purchase price [PLN]	Access to service [km]	Functionality level	Car type
1	very low	250,000	100	100	500
2	medium	300,000	40	100	700
3	very high	300,000	100	70	100
4	very high	250,000	70	40	300
5	high	250,000	40	130	100
6	low	150,000	70	100	100
7	low	100,000	40	70	300
8	very low	150,000	40	40	900
9	low	250,000	130	10	700
10	medium	150,000	100	10	300
11	low	300,000	10	40	500
12	low	200,000	100	130	900
13	high	300,000	70	10	900
14	high	200,000	10	100	300
15	very low	100,000	10	10	100
16	very low	200,000	70	70	700
17	medium	250,000	10	70	900
18	very high	150,000	10	130	700
19	very high	200,000	40	10	500
20	medium	100,000	70	130	500
21	high	100,000	100	40	700
22	very high	100,000	130	100	900
23	high	150,000	130	70	500
24	medium	200,000	130	40	100
25	very low	300,000	130	130	300

The same car profiles were used in the conjoint analysis in Ref. [51].

Table A4. Attributes of vehicles together with their corresponding partial utilities estimated through the conjoint analysis of consumers' preferences conducted in Ref. [51]

Engine type	Attributes	Levels and partial utilities				
HEV	safety level	very low	low	medium	high	very high
		−0.834	−0.591	0.175	0.577	0.672
	purchase price, PLN	100,000	150,000	200,000	250,000	300,000
		0.782	0.382	−0.018	−0.392	−0.753
	access to service, km	10	40	70	100	130
		0.166	−0.037	0.197	−0.281	−0.045
	functionality level	very low	low	medium	high	very high
		−0.345	−0.237	0.307	0.061	0.214
	car type	Urban	Compact	Sedan	SUV	VAN
		−0.247	0.047	−0.105	0.324	−0.018
PHEV	safety level	very low	low	medium	high	very high
		−0.706	−0.366	0.077	0.341	0.653
	purchase price, PLN	100,000	150,000	200,000	250,000	300,000
		0.694	0.257	0.014	−0.353	−0.612
	access to service, km	10	40	70	100	130
		−0.055	0.247	−0.078	0.056	−0.17
	access to charging, km	10	40	70	100	130
		0.223	0.283	0.076	−0.194	−0.388
	range, km	20	40	60	80	100
		−0.524	−0.254	−0.058	0.365	0.47
BEV	safety level	very low	low	medium	high	very high
		−0.927	−0.644	0.039	0.722	0.81
	purchase price, PLN	100,000	150,000	200,000	250,000	300,000
		0.741	0.463	−0.049	−0.361	−0.795
	access to service, km	10	40	70	100	130
		0.068	0.034	−0.19	0.039	0.049
	access to charging,	10	40	70	100	130
		0.039	0.049	0.098	0.039	−0.224
	range, km	100	300	500	700	900
		−0.663	−0.098	0.171	0.283	0.307

B. Grid-search calibration

B.1. Procedure

We run the simulations for $\alpha_{\text{PHEV}} \in \{4, 5, \dots, 14\}$ and $\alpha_{\text{BEV}} \in \{0, 0.1, \dots, 1.5\}$ and choose such a combination that minimizes the mean square error, given by equation (6). Since the survey does not provide any data to estimate the strengths of marketing for different vehicle types, we set $h_{\text{HEV}} = 0$, $h_{\text{PHEV}} = 0$, and $h_{\text{BEV}} = 0$, which corresponds to a scenario without marketing influence. Note, however, that the strengths of marketing can be included into the calibration procedure. Then, instead of setting them to zero, they become additional calibration parameters, which are estimated during the calibration process. However, optimizing five parameters using the grid search algorithm can be time-consuming. Therefore, we employ an alternative calibration algorithm for this purpose: the tree-structured Parzen estimator algorithm presented in the main text.

B.2. Results

Figure B1 illustrates the calibration procedure conducted for all the models: columns correspond to different networks, whereas rows to different initialization conditions. In each subplot, a red dot indicates values of α_{PHEV} and α_{BEV} that minimize the mean square error (MSE). These values are presented in Table B1, and they are used in further simulations. The MSE landscapes in Figure B1 are similar for the same initialization conditions regardless of the network structure. The calibration parameter α_{BEV} is around one order of magnitude smaller than α_{PHEV}, which is consistent with the calibration based on the tree-structured Parzen estimator algorithm, presented in the main paper. Figure B2 presents the time evolution of the calibrated models on a square lattice. Just after around five Monte Carlo steps, the simulated adoption levels (represented by symbols) start closely approximating the estimated adoption levels from the surveys (represented by horizontal solid lines), which is also consistent with the results based on the tree-structured Parzen estimator algorithm. Similar situation takes place in the case of the Watts–Strogatz networks. After calibrating the model, we examine how the strength of marketing affects the steady-state adoption levels of different AFVs. We compare the models calibrated to different networks and to different combinations of heterogeneous and homogeneous initial conditions.

Each panel of Figs. B3–B5 illustrates the results for the systems where we vary the marketing strength only for one vehicle type, and the marketing strengths for the remaining two types are set to zero. When all three marketing strengths are equal to zero, $h_{\text{HEV}} = 0$, $h_{\text{PHEV}} = 0$, and $h_{\text{BEV}} = 0$, all the models produce very similar results since they were calibrated under such conditions. However, as the values of these parameters increase, we observe an increase in the divergence of adoption levels. Again, as with the results from the tree-structured Parzen estimator algorithm, marketing strength is the most important factor influencing adoption in the given vehicle category. Again, at the macro level, the differences between the 12 models are not significant. The main difference between these results and those presented in the main paper concerns the role of the network. Here we see no significant difference between the square lattice and other networks.

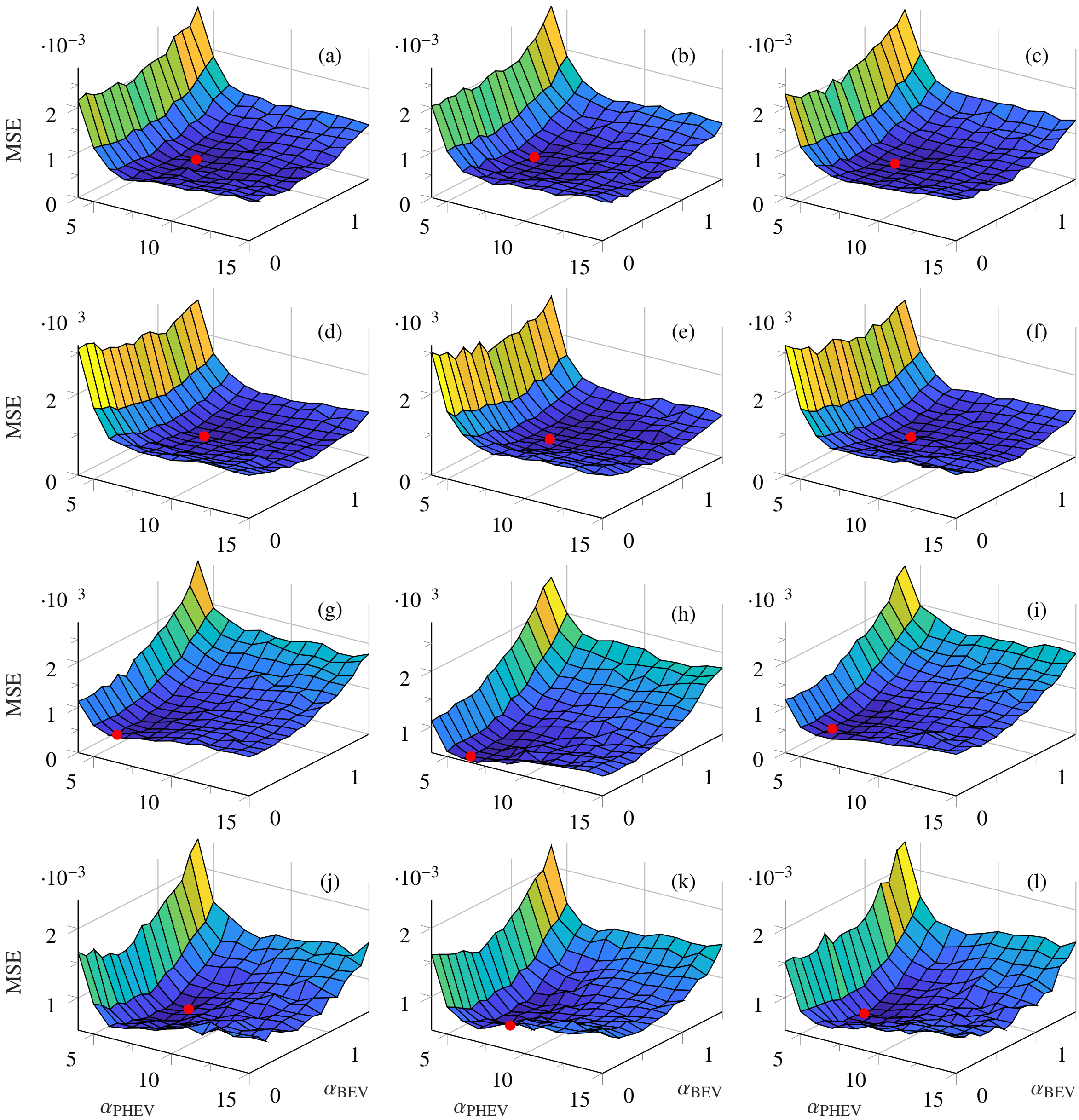

Figure B1. Mean square errors (MSE) obtained from our calibration procedure as a function of α_{PHEV} and α_{BEV} for different model setups. Networks: left column – square lattice with $N = 1024$ agents (32×32); middle column – Watts–Strogatz network with $N = 1024$ agents, $\langle k \rangle = 4$, and $\beta = 0$; right column – Watts–Strogatz network with $N = 1024$ agents, $\langle k \rangle = 4$, and $\beta = 1$. Initialization conditions: (a)–(c) homogeneous susceptibilities and driving patters, (d)–(f) homogeneous susceptibilities and heterogeneous driving patters, (g)–(i) heterogeneous susceptibilities and homogeneous driving patters, (j)–(l) heterogeneous susceptibilities and driving patters. Red points indicate the lowest values of MSE (Table B1)

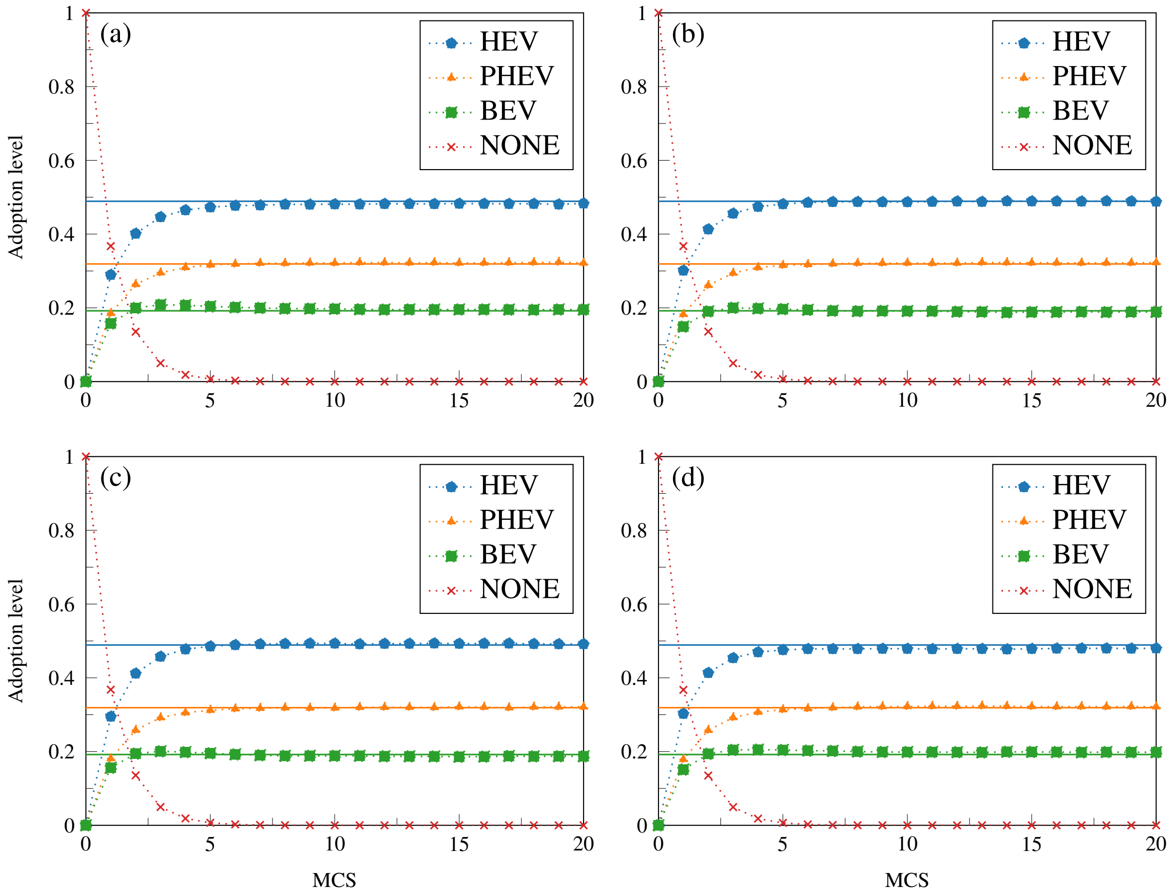

Figure B2. Time evolution of the adoption levels of AFVs for the models on a square lattice of $N = 1024$ agents (32×32) without marketing (i.e., $h_{\text{HEV}} = 0$, $h_{\text{PHEV}} = 0$, and $h_{\text{BEV}} = 0)\langle k \rangle = 4$, and for optimal values of α_{PHEV} and α_{BEV} (Table B1), obtained for different combinations of heterogeneous and homogeneous conditions: a) homogeneous susceptibilities and driving patterns, b) homogeneous susceptibilities and heterogeneous driving patterns, c) heterogeneous susceptibilities and homogeneous driving patterns, and d) heterogeneous susceptibilities and driving patterns. Symbols represent the average trajectory, and the error (SEM) bars are of the order of the symbol size. Horizontal continuous lines correspond to the percentages estimated in the survey [51] (Figure 5). NONE represents the fraction of agents without a car

Table B1. Parameters α_{PHEV} and α_{BEV} obtained form the calibration procedure based on the grid search for different model setups with the corresponding mean square errors (MSE)

Heterogeneous Susceptibilities	Heterogeneous Driving patterns	α_{PHEV}	α_{BEV}	MSE
Square lattice with $N = 1024$ agents (32×32)				
no	no	8	0.7	0.000556
no	yes	8	0.8	0.000532
yes	no	6	0.1	0.000479
yes	yes	7	0.8	0.000533
Watts–Strogatz network with $N = 1024$ agents, $\langle k \rangle = 4$, and $\beta = 0$				
no	no	7	0.7	0.000523
no	yes	8	0.7	0.000561
yes	no	6	0.1	0.000528
yes	yes	7	0.4	0.000506
Watts–Strogatz network with $N = 1024$ agents, $\langle k \rangle = 4$, and $\beta = 1$				
no	no	8	0.6	0.000555
no	yes	8	0.8	0.000515
yes	no	6	0.2	0.000519
yes	yes	6	0.6	0.000528

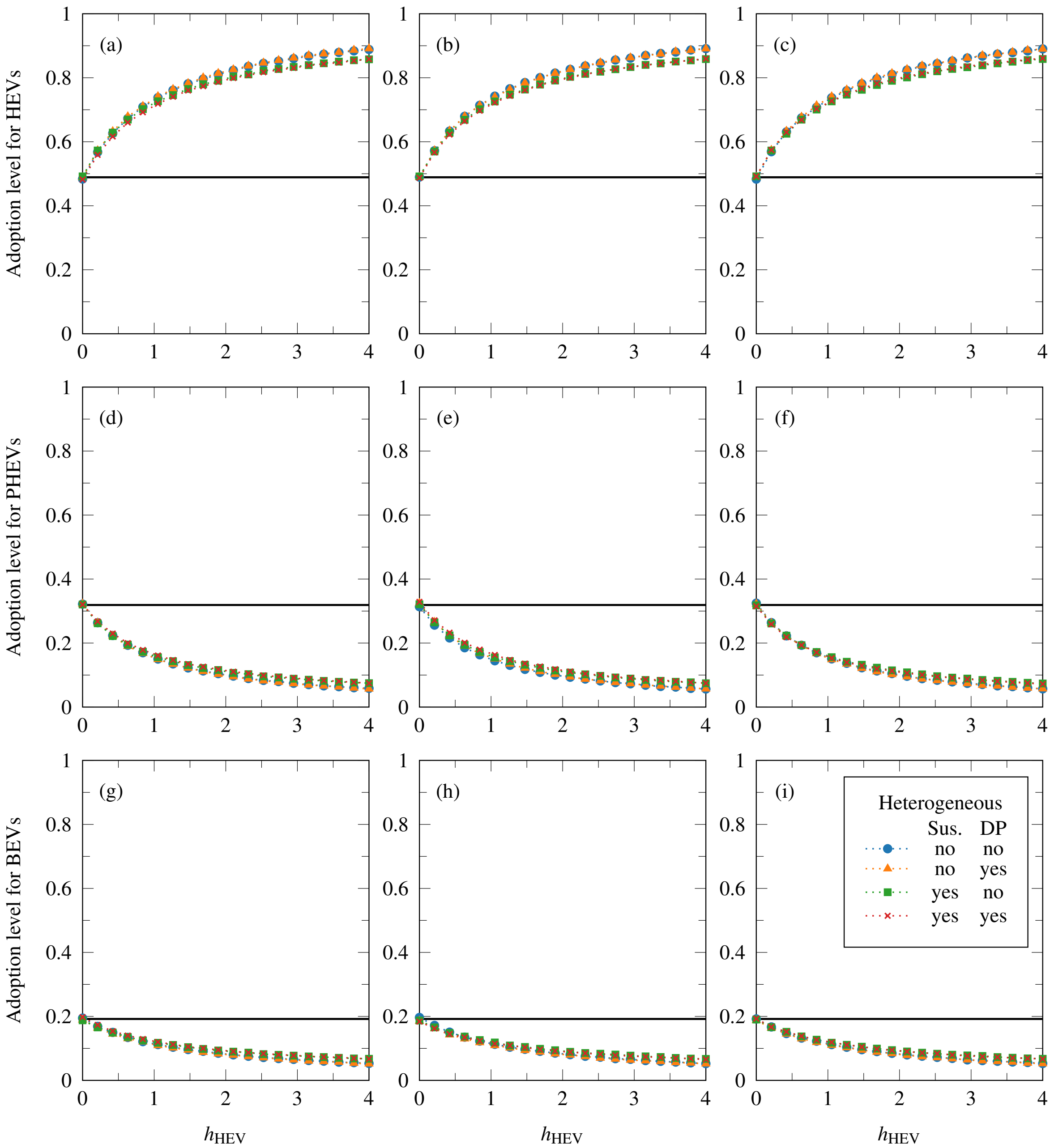

Figure B3. Comparison between the stationary adoption levels for (a)–(c) HEVs, (d)–(f) PHEVs, and (g)–(i) BEVs obtained for the models with different combinations of initialization conditions. Networks: left column – square lattice with $N = 1024$ agents (32×32); middle column – Watts–Strogatz network with $N = 1024$ agents, $\langle k \rangle = 4$, and $\beta = 0$; right column – Watts–Strogatz network with $N = 1024$ agents, $\langle k \rangle = 4$, and $\beta = 1$. Only the marketing strength for HEVs is varied, the rest of the marketing strengths are set to 0, i.e., $h_{\mathrm{PHEV}} = 0$ and $h_{\mathrm{BEV}} = 0$. Horizontal, continuous lines correspond to the percentages estimated in the survey [51] (Figure 5). The error (SEM) bars are of the order of the symbol size

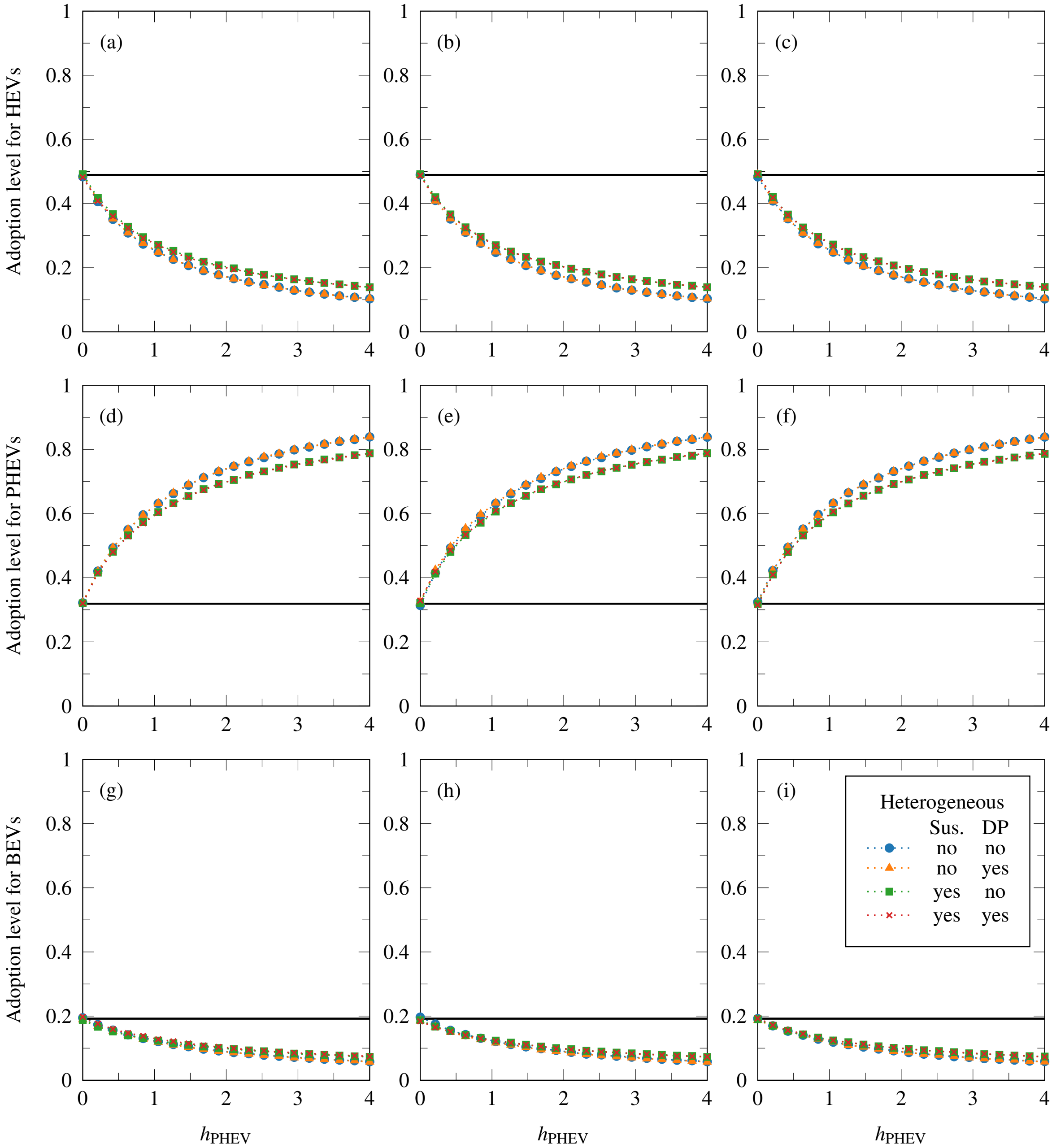

Figure B4. Comparison between the stationary adoption levels for (a)–(c) HEVs, (d)–(f) PHEVs, and (g)–(i) BEVs obtained for the models with different combinations of initialization conditions. Networks: left column – square lattice with $N = 1024$ agents (32×32); middle column – Watts–Strogatz network with $N = 1024$ agents, $\langle k \rangle = 4$, and $\beta = 0$; right column – Watts–Strogatz network with $N = 1024$ agents, $\langle k \rangle = 4$, and $\beta = 1$. Only the marketing strength for PHEVs is varied, the rest of the marketing strengths are set to 0, i.e., $h_{\text{HEV}} = 0$ and $h_{\text{BEV}} = 0$. Horizontal, continuous lines correspond to the percentages estimated in the survey [51] (Figure 5). The error (SEM) bars are of the order of the symbol size

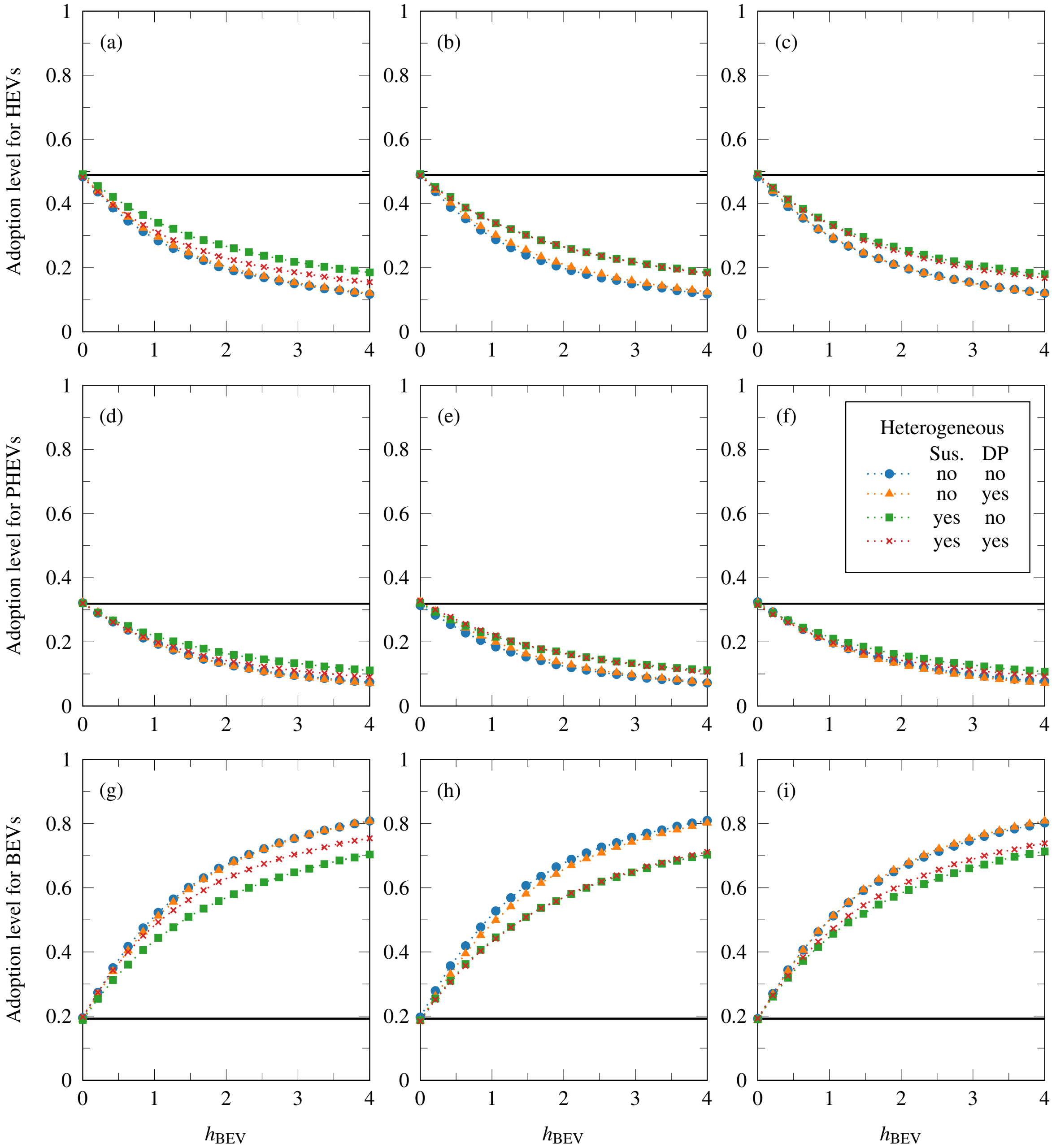

Figure B5. Comparison between the stationary adoption levels for (a)–(c) HEVs, (d)–(f) PHEVs, and (g)–(i) BEVs obtained for the models with different combinations of initialization conditions. Networks: left column – square lattice with $N = 1024$ agents (32×32); middle column – Watts–Strogatz network with $N = 1024$ agents, $\langle k \rangle = 4$, and $\beta = 0$; right column – Watts–Strogatz network with $N = 1024$ agents, $\langle k \rangle = 4$, and $\beta = 1$. Only the marketing strength for BEVs is varied, the rest of the marketing strengths are set to 0, ie., $h_{\text{HEV}} = 0$ and $h_{\text{PHEV}} = 0$.
Horizontal, continuous lines correspond to the percentages estimated in the survey [51] (Figure 5).
The error (SEM) bars are of the order of the symbol size