Agent-Based Modeling of Electric Vehicles Adoption: Assessing Sustainable Mobility from a Multi-Dimensional Perspective

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ABSTRACT

In recent decades, significant attention has been paid to air pollution and climate change, focusing on the centrality of mobility that plays a fundamental role in the emission of greenhouse gases. As a result, there is growing attention toward the electrification of road transport to achieve environmental sustainability (Kumar & Alok, 2020). The deployment of the adoption of electric vehicles seems to be an effective strategic policy in this direction. Therefore, scholarly research on this topic has witnessed a substantial increase in the current decade; however, such literature is mainly focused on different subsets of dimensions characterizing the phenomenon, leaving unexplored areas that comprehensively integrate the economic, technical, and social-behavioural elements of analysis, and delve into how all the corresponding variables interact with each other within a unique framework. In this paper, we propose an agent-based model (ABM) to investigate the adoption of electric vehicles (EVs) in a community of individuals. ABM is particularly indicated for modelling complex systems when the agents are affected by heterogeneity and not linear interactions (Cozzoni et al., 2021). Thus, we simulate the diffusion of adoption of EVs considering simultaneously the effects of technical aspects (driving range autonomy, purchasing price, operating costs, and the diffusion of charging infrastructure), economic incentives and social influence (financial support and advertising), and behavioural elements (range anxiety and environmental awareness). The interactions between agents occur along different topological structures (we examine Small-World and Scale Free network topologies) in which they act according to Kowalska-Pyzalska's model (Kowalska-Pyzalska, 2017). The model is partially calibrated using a sample of Italian consumers (Giansoldati et al., 2018a). Several simulative scenarios were implemented, varying the value of the variables involved. The analysis of the configurations showed some preliminary results, i.e., the large-scale adoption of EVs can be achieved by reducing range anxiety and increasing environmental awareness without using external forces such as financial supports and promotion. Similarly, increasing the values of the variables travel autonomy and diffusion of charging infrastructure. It was also noted that the effectiveness of financial support depends on the configuration of behavioural variables. Finally, the model has been implemented in NetLogo 6.1.1. It represents a general model that, in the future, research advancements could be specified for empirical cases and policy advice interventions.

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1. Introduction

As the importance of environmental safeguards grows, European countries are taking stronger actions to reduce air pollution and address climate change. Given the well-established correlation between the concentration of CO_2 in the atmosphere and global warming, the automotive sector plays a crucial role in achieving environmental sustainability (Kumar & Alok, 2020). With the well-known Green Deal and Fit for 55 programs, Europe has made formal commitments to achieve decarbonization within a specified timeframe; for example, it has been decreed to stop the production of gasoline and diesel-powered internal combustion engines by 2035[1]. Electric vehicles' adoption fits well with these targets, as witnessed by the exponential outgrowth related to e-fuel mobility technology. Hence, academic studies on this subject have experienced a significant increase in the last decade. Given the multifaceted nature of the transition to electric vehicles (EVs), it is challenging to encompass all aspects within a single model. Many models focus on specific aspects or subsets in order to serve particular research purposes, emphasizing the necessity for new approaches to address the challenges deriving from the growing environmental complexity (Ponsiglione et al., 2021). This work presents an ABM simulating the deployment of adoption of EVs, considering the effects of technical aspects, economic incentives, social influence, and behavioural elements simultaneously. From a practical perspective, it aims to be a typification applicable to specific concrete cases, analyzing the interaction between agents through two network typologies such as Scale free and Small world. The model is modularly designed to allow for future expansions. Furthermore, several simulative experiments were implemented, aiming for a better understanding of

[1] More information are available at https://www.consilium.europa.eu/en/

nonlinear dynamics in the consumers' decision-making process regarding the choice and adoption of such innovation to provide valuable insights for future research.

2. Relevance of the research

According to Kumar and Alok (2020), EVs are a complex issue encompassing many interconnected aspects. In their work, consumer preferences for EVs are influenced by a combination of different factors related to environmental, social, and economic dimensions. These factors differ from country to country and across cultures, reflecting the different political realities and ecosystems depending on EV types. For instance, He and colleagues (2014) studied hybrid electric vehicles adoption, including socio-demographics, the influence of social networks, vehicle usage, and vehicle specifications in their consumer choice model. Shafiei et al. (2017) created a system dynamics model of Iceland's energy system, considering energy markets, consumer choice behaviour, energy supply system, and refuelling infrastructure. Moreover, Javid and Nejat (2017) used a multinomial logit model to predict EVs adoption in California in order to reduce greenhouse gas emissions, whereas Karaaslan and colleagues (2018) investigated the impacts of EVs adoption on pedestrian safety by simulating a traffic intersection in Florida, implementing a 3D micro-simulation of an intersection in AnyLogic software. Liao and colleagues (2019) analyzed two business models, battery/vehicle leasing and mobility guarantee, providing a comparison of battery electric vehicles (BEVs), plug-in hybrid electric vehicles (PHEVs) and internal combustion engine vehicles. Later, Kaur and colleagues (2021) focused their attention on consumer attitude, examining the influence of knowledge on the adoption of EVs in India and considering the perceived risk, usefulness, and financial supports policies in their acceptance model. Overall, the transition to EVs involves various intertwined factors and requires comprehensive analysis. However, to the best of our knowledge, few studies have attempted to model the complexity of the issue, focusing on explicit or subset aspects in order to address specific research purposes; other research models are more empirical realities limiting the possibilities for generalization and theory development. As a result, there is a lack of research that provides a comprehensive understanding of the several factors associated with the adoption of EVs.

3. Contribution

According to the premises above, our paper aims to answer the following research question:

How do technical, social-behavioural, and economic factors interact to drive the adoption of EVs considering a consumer network?

To answer this question, we present an ABM aiming at encompassing various factors influencing the adoption of EVs in a community of individuals. ABM is particularly indicated when modelling complex systems and when the agents are affected by heterogeneity and not linear interactions (Cozzoni et al., 2021). Specifically, we consider the effects of driving range autonomy, purchase price, operating costs, the availability and expansion of charging infrastructure, financial support, advertising, range anxiety, and environmental awareness.

Therefore, our model aims to be a typification (Boero & Squazzoni, 2005), meaning a general model referring to a wide class of empirical situations that can be applied to particular cases if properly specified and validated. The modular structure we provide supports these future developments.

4. Method

To enhance a more organized representation of the model's components, we initially divided it into distinct blocks, including agents, the environment, and the interconnection mechanisms. Next, we translated each block into specific elements in the software code using NetLogo, providing a detailed description of the functions and operations within the model. In the following sections, we provide a detailed characterization of the main building blocks, further elucidating their components and functionalities.

The agents

Agents are individuals within a community who interact according to simple rules. In our model, they are represented by nodes interconnected in a graph, whose interactions occur along different topological structures (such as Scale Free and Small-World) in which they act according to Kowalska-Pyzalska's model (2017) that is described in the following sections. Moreover, the variables reported in Table 1 characterize each agent of the model.

Table 1: Agents' parameters

SYMBOL	DEFINITION
ea_i	Environmental awareness
a_i	Range Anxiety
$Pr_t^i\{EV\}$	EV choosing probability
$Pr_t^i\{CV\}$	CV choosing probability
$Pr_t^i\{purchase\}$	New vehicle purchase probability (constant)
$Pr_t^{average\_i\_linked}\{EV\}$	Average EV choosing probability
$N_t^{i\_high}$	Number of neighbours agents with higher choice preference than agent *i*
$N_t^{i\_low}$	Number of neighbours agents with lower choice preference than agent *i*
b_t^j	Impact due to social influence

Environment

The agents are surrounded by an environment in which some policies aim to facilitate EVs adoption. At the same time, the environment is also characterized by a topological structure of social relations among the agents. Here, the government's intervention is simulated by the variable representing financial supports (FS), which is incorporated into the probability update mechanism. Similarly, the variable h simulates the advertising and mass media influence the agents are exposed to.

Updating mechanisms

At each time step, the new vehicle purchasing probability for each agent is updated by checking whether the *i-th* agent has decided to purchase a new vehicle or not. In case he has decided to purchase a new vehicle, by examining EV choosing probability, it is determined whether he has decided to purchase a CV or EV. Otherwise, it is checked whether the agent is anxious or not, and based on whether the agent is surrounded by a higher or lower number of neighbours with a preference for EVs, the probability of choosing an electric vehicle by the *i-th* agent is modified. If all agents have purchased a new vehicle, the process ends. Instead, if there are agents who still need to purchase a vehicle, the new vehicle purchasing probability is re-evaluated.

The implemented model is threshold-based; thus, agents make a decision when the purchasing probability and purchasing probability EV exceed the predetermined thresholds (Kiesling et al., 2012). Figure 1 reports a flowchart visualizing the procedure for the updating mechanism concerning the change in consumer choice for EVs.

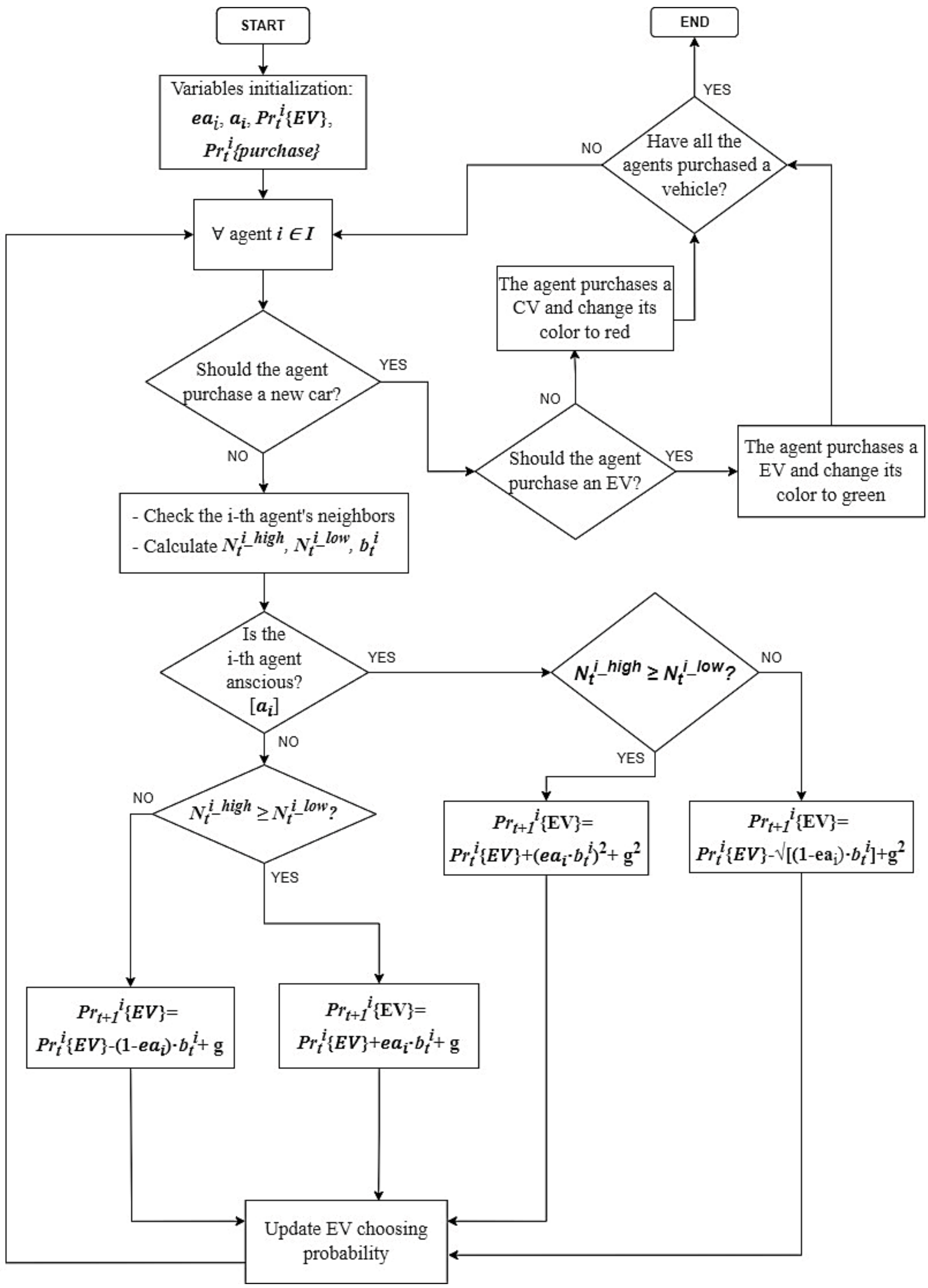

Figure 1: Updating mechanisms flowchart

5. Description of results

Different scenarios are obtained by varying the technical, behavioural, and external forces acting on the system. Scenario A is the baseline scenario, in which the variable values are reported according to Giansoldati (2018b). Scenario B hypothesizes that driving range and the diffusion of charging infrastructure are higher, while the purchase price is lower. For this reason, the average EV choosing probability in scenario B is always higher than that of scenario A under the same conditions.

Table 2: Technical, economic, and social variable values for different simulation scenarios

	Purchase Price [€]	Driving Range [Km]	Total Cost of Ownership	% Charging Infrastructure	% Anxious	FS	h	Average Environmental Awareness
Scenario A	30.000	250	2.500	20%	20; 30; 40; 80	0; 0.01; 0.02	0; 0.07	0.2; 0.5; 0.8
Scenario B	20.000	500	2.500	60%	20; 30; 40; 80	0; 0.01; 0.02	0; 0.07	0.2; 0.5; 0.8

Two threshold values have been defined for the behavioural variables: A=20 and $E[eai]$≈0.5. Their combination results in four main configurations, as shown in Table 3.

Table 3: Four analysis configurations

	% A	$E[eai]$
Hostility	> 20%	< 0.5
Indifference	≤ 20%	≈0.5
Segmentation	> 20%	> 0.5
High Willingness	≤ 20%	> 0.5

The simulation scenarios' analysis has yielded some preliminary results.

Supposing no external forces, social impact will strongly influence the system. This means that only when environmental awareness is high and range anxiety is low [High Willingness scenario], significant adoption of electric vehicles is achieved. In the other cases, it is negligible

[Hostility and Indifference scenarios], or it depends on the percentage of anxious individuals [Segmentation Scenario].

The effectiveness of financial supports is proportional to environmental awareness and range anxiety level: higher values of these two factors result in greater benefits [Segmentation configuration]. However, holding the environmental awareness level constant, the effectiveness decreases as the percentage of anxious individuals decreases [High Willingness configuration]. Finally, financial supports are less effective for high range anxiety and low environmental awareness [Hostility configuration]. In the Indifferent scenario, some improvements can be obtained.

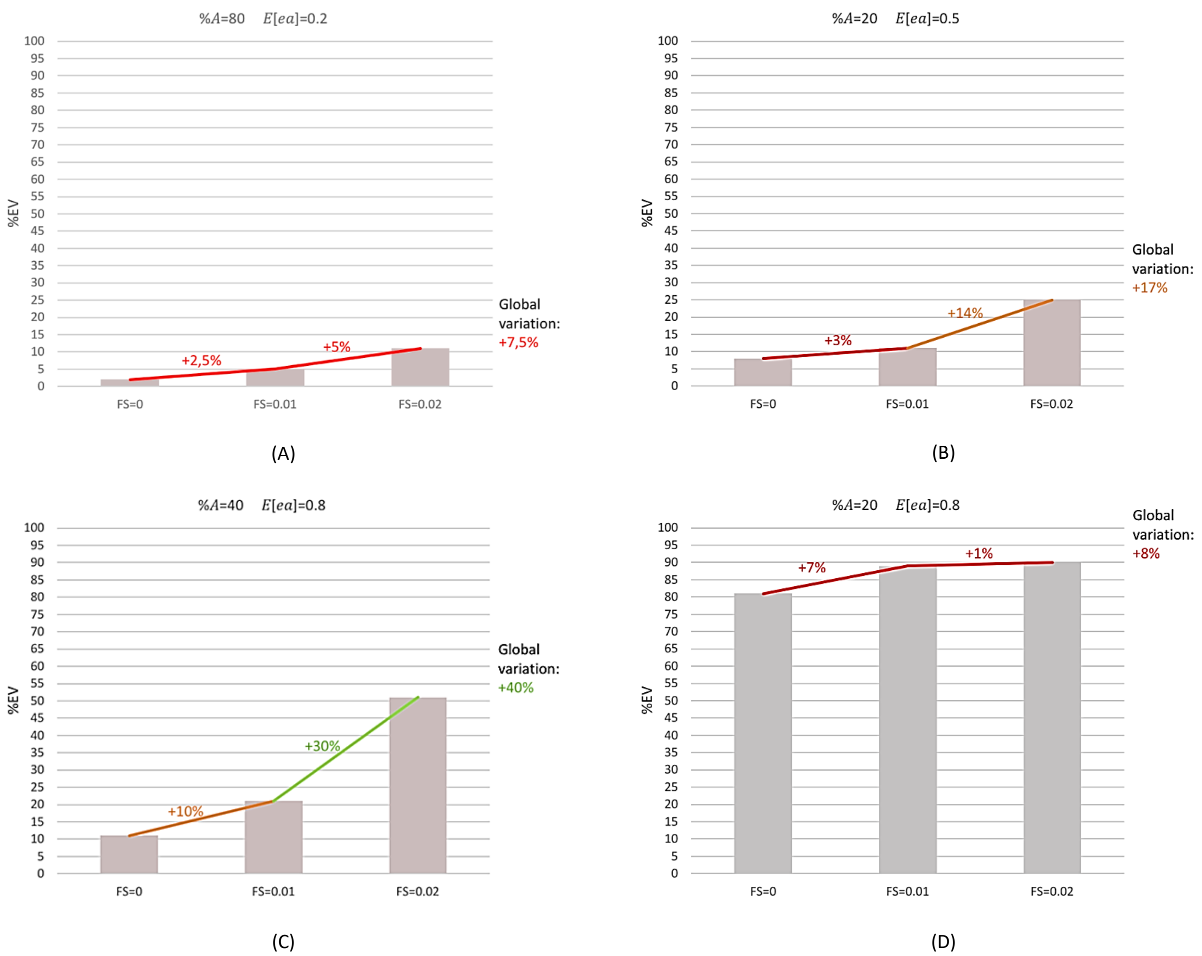

Fig.2: Experimental results for different scenarios (A) Hostility configuration, (B) Indifference configuration, (C) Segmentation, and (D) High Willingness configuration.

The model has to be validated, and further experiments will be presented in the final version of the work.

One limitation of this research is the lack of external validation. Furthermore, the inherent nature of the study, which involves typification, also poses limitations. Future works will include studying various network topologies such as multi-topologies and considering larger networks with over 100 agents. Additionally, using more recent data, especially related to events like Covid-19 and the Russian War, can help understand the phenomenon better. It is essential to compute the coefficients of technical, behavioural, and external variables, which might have different roles in different geographical contexts. Another aspect to explore is modelling the interrelations between EVs diffusion and other mobility transitions, such as automated vehicles, bike sharing, and car sharing. Lastly, distinguishing between PHEVs and BEVs within the EV category and assessing consumer preferences towards these specific vehicle types would provide valuable insights into the market.

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