Driving Decarbonization: Multidimensional Assessment through Agent-Based Modelling of Electric Vehicle Adoption

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Abstract – To meet the environmental sustainability objectives outlined in the Green Deal and the "Fit For 55" climate package, notably achieving carbon neutrality, European nations must curtail their greenhouse gas emissions. In this vein, promoting the adoption of electric vehicles emerges as a pivotal strategy. Previous research has primarily focused on isolated aspects of this phenomenon, neglecting a holistic approach that merges technical, socio-behavioural and external-related dimensions and their interrelations within a singular analytical framework. The present paper addresses this gap by developing an empirical agent-based model of electric vehicle adoption in a community of individuals, evaluating simultaneously the interplay of these aspects. Our findings demonstrate how factors like range anxiety and environmental awareness influence the rate of EV adoption. Additionally, we discuss the importance of driving factors such as government financial incentives and advertising expenditure in promoting EV adoption rates. By providing insights into the dynamics surrounding the adoption of EVs, this paper highlights the importance of employing a thorough policy framework to encourage the widespread implementation of sustainable practices.

Keywords – Agent-based modelling, electric vehicle, innovation adoption, environmental sustainability, alternative mobility.

1. Introduction

Meaningful momentum toward the CO2 net zero emission target is building (El Sayed et al., 2023). The current transition speed is insufficient to reach the 1.5˚C target established at the Conference of the Parties (COP 26) in 2021 (Paris Declaration, 2015), increasing the risks and impacts of climate change. The transportation sector, responsible for emitting approximately 21 per cent of the world's total CO2 emissions in 2020, is not on pace to achieve that reduction (Van Gogh Margi et al., 2022). The European Union's "Fit for 55" climate package of regulatory proposals—which aims to reduce emissions by 55% in 2030 compared with 1990 levels— will likely have long-term consequences for the transport sector. With this program, Europe has made formal commitments to achieve carbon neutrality by 2050. Most of the CO2 emission reductions until 2030 will come from technologies currently on the market. However, by 2050, about half of the reductions will come from technologies now in the demonstration or prototype phase (International Energy Agency, 2021). There is no single strategy for achieving a carbon-neutral transportation industry (Connolly et al., 2014), and a shift to electric vehicles (EVs) is frequently argued to be the best option (Paris Declaration, 2015). The industry has attracted more than $400 billion in investments over the last decade — with about $100 billion coming since the beginning of 2020 (Holland-Letz Matthias et al., 2021). Accordingly, over the past decade, there has been a significant increase in academic studies on this subject, with a growing emphasis on analysing the variables influencing the adoption of EVs, highlighting a contemporary concern within the context of environmental sustainability (Maybury et al., 2022). Given the multifaceted nature of the transition to 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, emphasising the necessity for new approaches to address the challenges deriving from the growing environmental complexity (Ponsiglione et al., 2021). With the current study, we aim to fill this gap by developing an agent-based model (ABM) simulating the process of EV adoption, considering the effects of technical, behavioural, and external forces-related variables in a unique framework. The paper is organised as follows. To better understand the field of research and the variables involved in EV adoption, an explorative literature review is conducted in section 2. Based on this theoretical knowledge, section 3 presents our modelling framework and methodology. Then, we outline the experimental design of the model (section 4) and report the results and discussion of the agent-based simulation in section 5. Finally, section 6 summarises our research, addresses the limitations of our study, and suggests potential extensions for future work.

2. Literature Background

In recent years, the literature on EVs has grown at an exponential rate due to the rapid development of electric mobility-related technologies (Kumar & Alok, 2020). EV adoption is a complex technological transition since many interconnected factors are involved. The variables associated with EV adoption have been studied extensively in the literature, and they could be categorised into three groups: technical, behavioural, and external. The technical dimension primarily focuses on the economic feasibility of EVs, analysing multiple dimensions of vehicle attributes and cost structure, like purchasing price, maintenance cost, operation cost, depreciation, and energy prices. Research in this area, like studies by Giansoldati et al. (2018), has compared EVs with petrol cars based on technical features such as driving range, purchase price, and annual operating costs. Further examination by Scorrano et Danielis (2022) includes additional variables like fuel economy, the time required for a fast charge, and the hours of free parking in urban areas. Zhuge et al. (2019) differentiate between upfront and operative costs, providing a comprehensive view of the economic factors influencing EV adoption. Conversely, the behavioural dimension explores how psychological aspects, such as range anxiety and environmental awareness, influence consumers' willingness to adopt EVs (Dimitropoulos et al., 2013; Kumar & Alok, 2020; Melliger et al., 2018). Skippon et al. (2016) found that adoption intentions decrease after users' experience driving low-range EVs, while Smith et al. (2017) highlighted how environmental awareness is a powerful motivator for EV adoption, with potential environmental benefits being a key driver in consumer decision-making. Finally, the external dimension related to the environment or policy includes variables like financial support, advertising, and free parking. Kowalska (2017) demonstrated that increased financial support and effective advertising can quickly enhance consumer willingness to pay and accelerate EV adoption. Other research, like Mersky et al. (2016), indicated that free parking and other toll exemptions are not significant predictors of EV adoption. Despite the important contribution of such scientific results, a holistic "whole system approach" is needed to address the multifaceted nature of EV adoption effectively. This approach should simultaneously consider all dimensions—technical, behavioural, and external—to understand their interactions and the collective impact on the adoption process. However, it is challenging to encompass all aspects within a single model. To the best of our knowledge, there is a lack of research that provides a comprehensive understanding of the impact of the several factors associated with the adoption of EVs. According to the premises, our paper aims to answer the following research question:

How do technical, social-behavioural, and external variables affect EV adoption considering a consumer network?

To answer this question, the present work proposes an ABM aiming at encompassing these variables simultaneously into a unique framework that is then analysed by exploiting calibrating scenarios based on previous surveys on consumer preferences conducted by Danielis and colleagues (Danielis et al., 2020; Giansoldati et al., 2018; Scorrano & Danielis, 2022; Valeri & Danielis, 2015). The study's novelty lies in the multidimensional perspective of the sustainable mobility assessment, which contributes to a more comprehensive understanding of consumer decision-making processes.

3. The modelling framework and methodology

This section explains our study's underlying ABM approach and modelling framework in detail, including fundamental building blocks like the agents, environments, and updating mechanism. Below, we will discuss each of these building blocks.

3.1 Agent-based modelling

An ABM is a computational technique to study complex adaptive systems' emerging properties or aggregate behaviours (Gilbert & Terna, 2000). The adoption of ABM stems from its bottom-up approach, meaning individual agents are assigned specific attributes. Autonomous cognitive agents interact with resources, limitations, and other agents as members of a relational network operating within a virtual environment (Bonabeau, 2002). Self-organised collective behaviour emerges over time into a coherent form and adapts itself without any singular entity deliberately managing or controlling it (Holland, 1995). As Cozzoni et al. (2021) pointed out, the environmental nonlinear interactions and agent heterogeneity at the core of ABM set it apart from other modelling methodologies, making it particularly suitable for modelling complex adaptive systems. Over the last decade, there has been an increasing interest in using ABM to simulate and model individuals' behaviour and automobile purchasing decisions (Barter et al., 2015; Dunkin et al., 2009; Huang et al., 2021; Neshat et al., 2023; Silvia & Krause, 2016; Zhuge & Shao, 2019). In this paper, we employ ABM due to its capability to capture the emergent phenomenon of EV adoption, to give a natural description of a system made of "behavioural" entities and to its adaptability across several dimensions.

3.2. Model Description

To assess EV adoption, we apply a framework developed by Danielis et al. (2020) and Giansoldati (2018), who surveyed consumers' preferences in Italy in 2018. In our model, the agents make EV or CV purchasing decisions to maximise their utility based on a combination of variables weighted according to Giansoldati and Danielis' coefficients. The range of potential variables is extensive and varies significantly in terms of their metrics. We selected the following variables: purchase price, fuel economy, driving range, the time required for a fast charge, the maximum distance between fast charging stations, free parking, range anxiety, environmental awareness, financial support, and advertising. Table 1 lists all variables, their ranges, and measurement units. The brand/model coefficients are not implemented in the ABM. The adoption process occurs within a Scale-Free network formed by constantly adding new vertices to the system. As a result, the network's total number of vertices increases over time.

Table 1: Model's variables

Type	Variable	Range	Unit
Technical	P^{EV} [Purchase price]	34.000-60.000	€
	FE^{EV} [Fuel economy]	0,03-0,08	€/100km
	R^{EV} [Driving range]	290-510	km
	FC^{EV}[Fast charging time]	18-70	min
	M^{EV}[Max distance btw charging stations]	20-80	Km
Behavioural	a_i [Range Anxiety]	0-1	%
	ea_i [Environmental awareness]	0-1	%
External Forces	FS [Financial support]	0-100	%
	h [Advertising]	0-100	%
	FP^{EV} [Free Parking]	0-24	hours

To build a more structured representation of the model, we first divided it into distinct blocks: agents, the environment, and the interconnection mechanisms. Next, we used Netlogo to break down each block into individual components inside the software code, providing a detailed description of the functions and operations within the model. Figure 1 introduces the framework that works step by step (weekly) in the software environment.

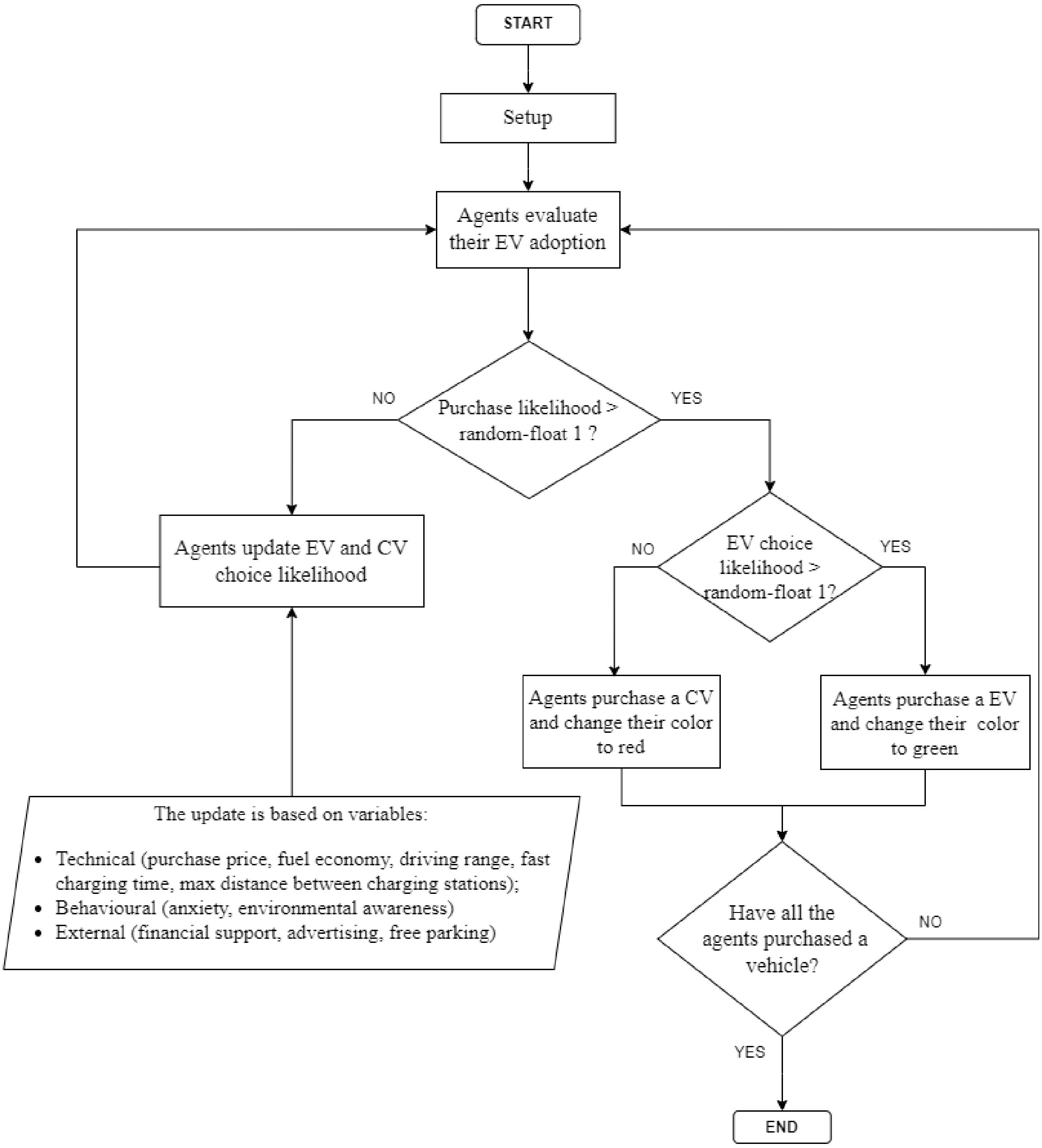


Figure 1: Illustration of the process flow chart.

3.3.1 Agents

Agents are members of a community who interact following simple rules. In our model, they are represented as nodes in a graph whose interactions occur along a Small-World topological structure. Each agent chooses between EV and CV according to its likelihood thresholds, based on Kowalska-Pyzalska's model (2017). The variables reported in Table 2 characterise the agents of the model.

Let I be the set of all agents in the system, A be the set of anxious agents, and NA be the set of non-anxious agents. Therefore, $I = A \cup NA$. This work employs the multinomial logit as a choice model to describe consumer's choice likelihood.

Specifically, it is a binary logit model since there are two alternatives (EV or CV). The structure of the choice likelihood is based on Danielis's research (2020):

$$Pr_i\{EV\}= \frac{e^{V_{EV,i}}}{e^{V_{EV,i}}+e^{V_{CV,i}}}$$

where V_{EV} and V_{CV} are the systematic utility functions (i.e. not including the error term). Assuming a utility-maximising behaviour (Uncles et al., 1987), an agent selects a vehicle alternative (EV or CV) when that alternative yields the highest possible level of utility.

The CV choice likelihood is complementary to the electric one:

$$Pr_i\{CV\} = 1 - Pr_i\ \{EV\}$$

Table 2: Agents' parameters

Symbol	Definition
ea_i	Environmental awareness
a_i	Range Anxiety
$Pr_t^i\{EV\}$	EV choice probability
$Pr_t^i\{\mathrm{CV}\}$	CV choice probability
$Pr_t^i\{\mathrm{purchase}\}$	New vehicle purchase probability (constant)
$Pr_t^{average\_i\_linked}\{EV\}$	Average EV choice 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

3.3.2 Environment

The environment is fundamentally represented by government and social media. The agents are surrounded by a network in which some policies and advertising aim to facilitate EV adoption. Here, the government's intervention is simulated by the variable FS. Similarly, the variable h simulates the advertising and mass media influence the agents are exposed to. Their contribution to the agent's EV choice likelihood is computed according to Kowalska-Pyzalska's research as follows:

$$g = (0.4FS + 0.1h)$$

These parameters can be modified through a slider in the software interface. Increasing their values allows for the simulation of a stronger government or social media intervention.

Social influence is conveyed as network homophily: if more EV-preferential neighbours than CV-preferential neighbours surround the agent, the agent's EV choice probability is shifted toward EV and vice versa. In analytical terms, the number of i-th agent's neighbours with EV choice probability higher ($N_t^{i\_high}$) and lower ($N_t^{i\_low}$) than his own current $Pr_t^i\{EV\}$ are computed. Then, the average of $Pr_t^i\{EV\}$ of the agent's neighbours ($Pr_t^{average\_j\_linked}\{EV\}$) is calculated. Finally, according to Kowalska-Pyzalska's research, social influence is computed as follows:

$$b_j^t = (0.5Pr_t^{average\_j\_linked}\{EV\})$$

3.3.3 Updating mechanisms

At each time step, the probability that each agent will purchase a new vehicle is updated. This process begins by checking if the i-th agent has decided to buy a new vehicle. If the agent has opted to buy, the likelihood of choosing an EV or a CV is assessed. If the agent has not decided to purchase, the analysis shifts to the agent's anxiety level. The probability of the i-th agent choosing an EV is then adjusted based on whether it is surrounded by a higher or lower number of neighbours who prefer EVs.

In analytical terms, at each step, every agent $i \in NA$ (ai=0) updates its EV choice likelihood according to the following equation:

$$Pr_{t+1}^i\{\mathrm{EV}\} = \begin{cases} Pr_t^i\{\mathrm{EV}\} + ea_i \cdot b_t^i + g & if\ N_t^{i\_high} \geq N_t^{i\_low} \\ Pr_t^i\{\mathrm{EV}\} - (1 - ea_i) \cdot b_t^i + g & if\ N_t^{i\_high} < N_t^{i\_low} \end{cases}$$

In the case of anxious agents $j \in A$ (a_i=1), EV choice likelihood will be updated according to the following equations, considering a more considerable inclination to reduce EV preference:

$$Pr_{t+1}^j\{\mathrm{EV}\} = \begin{cases} Pr_t^j\{\mathrm{EV}\} + (ea_j \cdot b_t^j)^t + g^2 & if\ N_t^{j\_high} \geq N_t^{j\_low} \\ Pr_t^j\{\mathrm{EV}\} - \sqrt{(1 - ea_i) \cdot b_t^j} + g^2 & if\ N_t^{j\_high} < N_t^{j\_low} \end{cases}$$

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.

3.3.4 Model validation

Validation has always been critical in modelling efforts (Conway et al., 1959), particularly in computational models, such as ABMs (Carley, 2017; Garcia et al., 2007). However, the lack of a broadly approved technique is a substantial problem for validation. There are several validation procedures and principles in the literature, and different levels of validation may be accomplished. To date, we applied an internal validation, comparing quantitatively the EV choice average preference and the number of EVs purchased at the end of the simulation with the results from the Kowalska-Pyzalska's model for different values of the agents' parameters.

3.3.5 Model calibration

The model's calibration was based on Danielis's stated preference study, which examined consumers' decisions between buying gasoline-powered and EVs (Danielis et al., 2020). The mixed logit model was generated using interviews conducted in Friuli-Venezia Giulia, Italy, in 2018.

4. Experimental design

Starting from Danielis's research (2020), which focuses on five popular electric vehicle (EV) models in Italy during 2018 (BMW i3, VW eGolf, Renault Zoe, Nissan Leaf, and Daimler Smart For Four ED), this study updates these models to their 2023 versions to develop scenarios. According to that, Table 3 lists the parameter values for these updated 2023 EV models. Fuel economy (FE) varies based on the type of energy company subscription. Refuelling at fast charging stations with direct current averages approximately 0.6 €/kWh1. Fast charging times are based on 43 to 50 kW direct current charging stations, the most common in Italy2. Specific recharge times from 10% to 80% battery capacity are provided. Given the "Fit for 55%" package's objectives for charging infrastructure development (60km), and as a prudent measure, the maximum distance between charging stations has been set at 80 km.

Table 3: EVs' parameters

EV type	P^{EV} (euro)	FE^{EV}(euro/km)	R^{EV}(km)	FC^{EV}(min)	M^{EV}(km)
BMWi3 (2022/2023)[3]	41100	0,07	296	42	80
VW id3[4]	43600	0,03	486	35	80
Renault zoe - Equilibre R110[5]	33500	0,08	395	70	80
Smart #1	42548	0,08	440	30	80
Hyundai IONIQ 5[6]	59350	0,03	507	18	80

Thus, Table 4 shows the baseline technical scenario built using the average of the variables collected in Table 3.

[1] https://www.wemedia.it/faq/quanto_costa_un_kwh_per_auto-120.html#:~:text=In%20generale%2C%20il%20costo%20medio,installazione%20di%20un%20caricatore%20domestico.

[2] https://www.leaseplan.com/it-it/news-auto/sostenibilita/colonnine-elettriche-italia/#:~:text=La%20maggior%20parte%20di%20essi,di%2022%20kW%20sono%2034.485.

[3] https://www.bmw.it/it/gamma/bmw-i/i3/2021/panoramica-bmw-i3.html

[4] https://www.automobile.it/magazine/recensioni-modelli/volkswagen-id-3-23080#:~:text=Quando%20si%20parla%20della%20Volkswagen,secondo%20quanto%20dichiarato%20dalla%20casa.

[5] https://www.alvolante.it/listino_auto/renault-zoe

[6] https://www.hdmotori.it/hyundai/test-batteria/n555156/hyundai-ioniq-5-rwd-prova-consumi-reali-72-kwh/

Table 4: Baseline Technical Scenario

Scenario	P^{EV} **(euro)**	FE^{EV}**(euro/km)**	R^{EV}**(km)**	FC^{EV}**(min)**	M^{EV}**(km)**
Baseline Technical Scenario 2023	44000	0,06	400	44	80

We developed five configurations to examine the impact of two variables: range anxiety and environmental awareness. In some configurations, we maintained range anxiety at its average level while increasing environmental awareness. In others, we kept environmental awareness constant and decreased range anxiety. These configurations are detailed in Table 5. The average percentage of anxious agents is 35% based on surveys conducted by Ernst &Young (Samant et al., 2022). Environmental awareness is derived from a normal distribution with a 0.05 standard deviation and the mean value based on Danielis's survey (2020).

Table 5: Range anxiety and Environmental awareness levels

Scenario	**%A**	**E[ea$_i$]**
1.1	35	0,6
1.2	25	0,6
1.3	15	0,6
1.4	35	0,75
1.5	35	0,9

In Italy, various incentives have been introduced to encourage the purchase of EVs. Governed by decree-law no. 17/2022, the 2023 incentives for EVs apply only to the purchase of new vehicles. Buyers can receive an incentive of 5,000 euros (FS=21) if they plan to scrap an old vehicle or 3,000 euros without scrapping (FS=7). Since no references exist in the literature, we use average and maximum values for h. The experimental configurations are detailed in Table 6.

5. Simulation Results and Discussion

We find that considering no external forces, EV adoption is inversely proportional to range anxiety and directly proportional to environmental awareness. Specifically, a decrease in range anxiety significantly boosts EV adoption: a 10% reduction almost doubles the adoption rate (32%), while a 20% reduction can triple it (53%). Figure 2 illustrates the impact of a gradual decrease in range anxiety on the rate of EV adoption. Similarly, increasing environmental awareness also correlates with higher EV adoption rates. An increase of 25% in environmental awareness raises the adoption rate to 27%, and a 50% increase pushes it to 66%. Figure 3 illustrates the impact of environmental awareness on EV adoption, supposing a gradual increase.

Table 6: Experimental configurations

	Behavioural Variables		External forces		
	%A	E[ea]	FS(%)	h(%)	$FP^{EV}(h)$
	35	0,60			
1	25	0.75	0	0	0
	15	0.90			
2	35	0,6	7	0	0
3	35	0,6	21	0	0
4	35	0,6	0	50	0
5	35	0,6	0	100	0
6	35	0,6	0	0	12
7	35	0,6	0	0	24
8	35	0,6	7	50	12
9	35	0,6	21	100	24

Figure 2: Range Anxiety impact on EV adoption

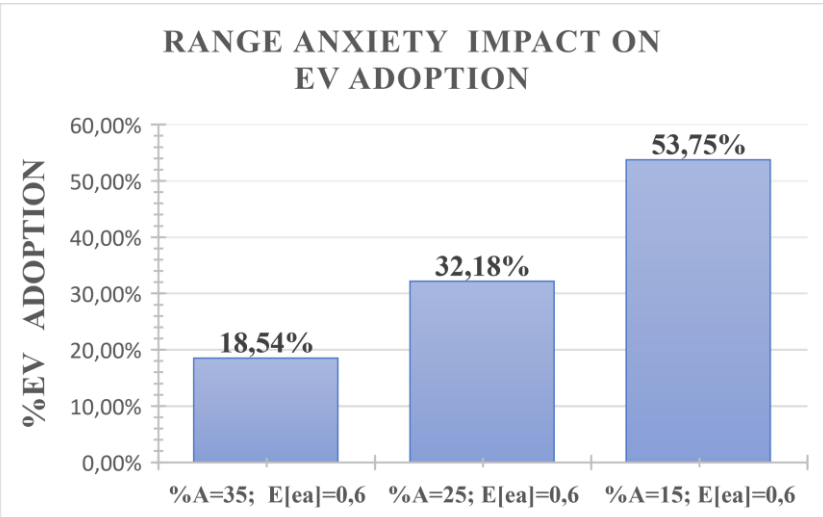
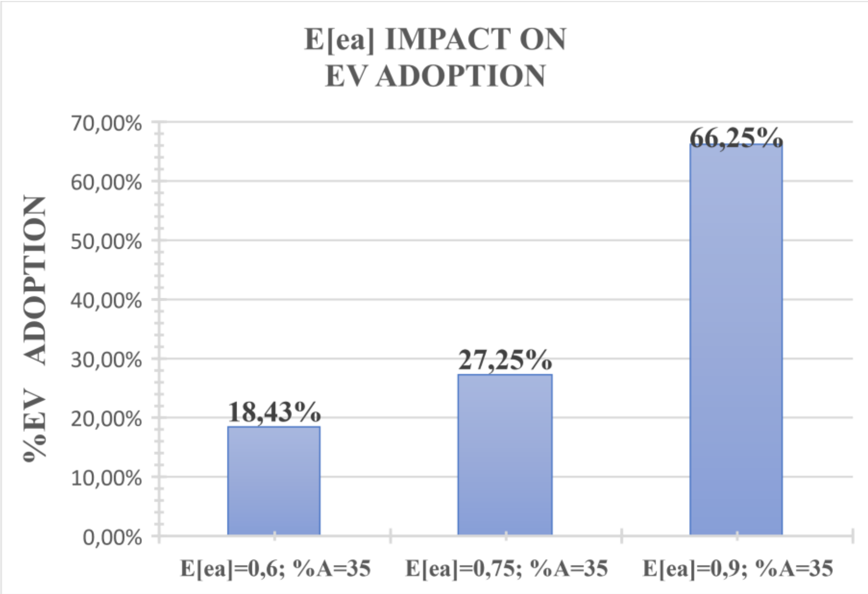
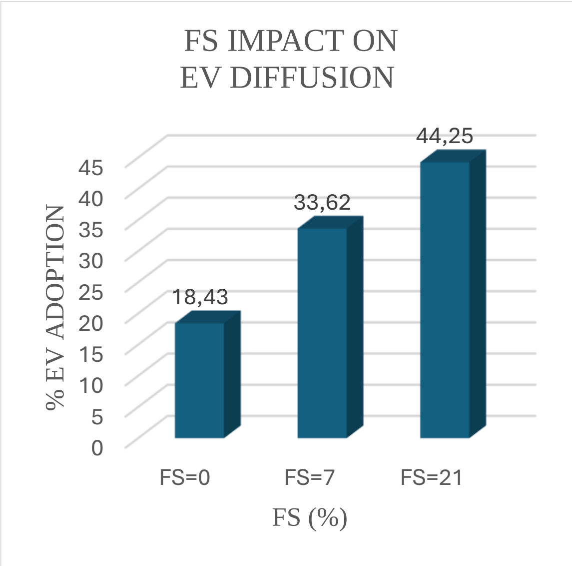


Figure 3: Environmental Awareness impact on EV adoption

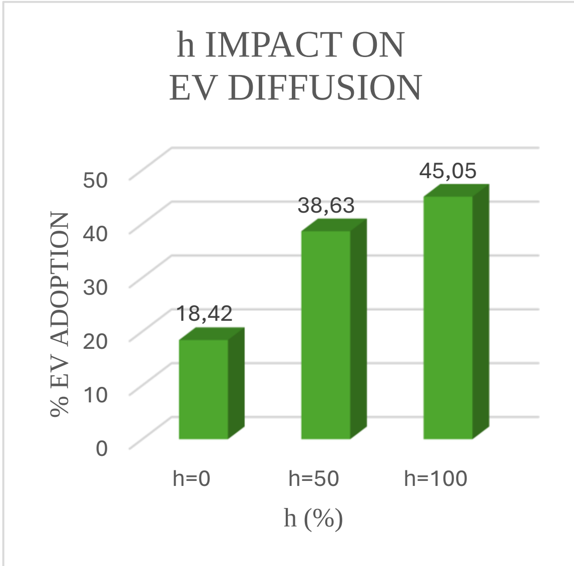


We found that a 7% increase in government financial incentives can boost the average European EV adoption rate from 18% to 34%. However, even tripling these incentives yields a rise to 44%, suggesting diminishing returns. Similarly, doubling advertising expenditure can raise adoption from 18% to 38%. Maximising the variable h further increases the adoption rate to 45%. In contrast, the influence of free parking on adoption appears minimal. At its maximum value, the free parking variable (FP) only enhances the EV adoption rate by a modest five percentage points. Figure 3 shows the variation in EV adoption rates for different levels of financial support, advertisement and free parking. Our simulations show that combining these forces at their average levels yields an EV adoption rate of approximately 45%, comparable to scenarios where each variable operates independently at its maximum intensity (42-43%). Table 7 shows EV adoption supposing external forces at medium and highest levels.

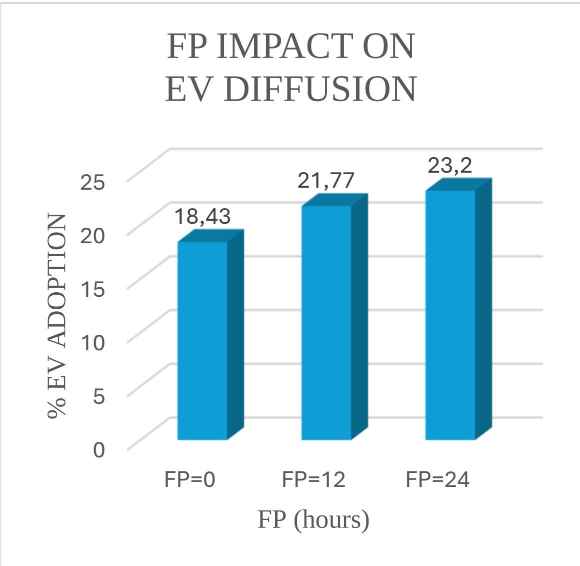
Despite the challenges posed by the European adoption threshold, accelerating EV adoption requires a multifaceted strategy, including mass-media advertising, education, technology development, and enhanced financial support to build a critical consumer base. These findings are consistent with the results of Melliger et al. (2018) and Quak et al. (2016) but differ from those of Zhuge and Shao (2019). They found that environmental awareness accounted only for 9.6% of the total, compared with vehicle price, usage, social influence, purchase restriction, and traffic restriction.



(a)



(b)



(c)

Fig.3: Experimental results for different levels of:

(a) financial support [FS],

(b) advertisement [h],

(c) Free Parking [FP]

Table 7: EV adoption in the best conditions

%A	E[ea]	FS(%)	h (%)	FP (h)	% EV ADOPTION
35	0,6	7	50	12	42,43
35	0,6	21	100	24	51,42

This result is due to the parameters' weights strongly related to socio-demographic characteristics, such as individual income, education level, survey administration region, and modelling variables. Although it can be complex to influence these variables, range anxiety antecedent analysis has often been carried out (Kumar & Alok, 2020). Investments in battery technology, driving range, and charging infrastructure are crucial to mitigate these concerns (Giansoldati et al., 2018; Krishna, 2021; Pillai et al., 2022). On the other hand, public acceptance, which is positively influenced by EVs' environmental performance, is a critical driver for market penetration (Smith et al., 2017). Enhancing public awareness through marketing strategies and educational programs can significantly boost environmental awareness and, subsequently, EV adoption. Investments in external factors like financial support and advertising are also vital, as they have been shown to produce similar adoption rates as maximising individual factors(Kowalska-Pyzalska A., 2017; Kumar & Alok, 2020; Maybury et al., 2022; Scorrano & Danielis, 2022). Further quantitative research is needed to estimate better marketing costs and the relative effects of advertising strategies. A simulated scenario shows that a medium-level mix of advertising and financial support achieves the exact adoption rate of EVs by maximising each variable separately. A balanced approach to policy making, which avoids overemphasising any single variable such as free parking—shown to have minimal impact on adoption rates—is recommended. Regarding methodology, ABM allows variables from many dimensions to be integrated into a single model and evaluates how they affect EV adoption, capturing decision-making's complex and non-deterministic nature. This is an essential message for policy planning in general. If it is acknowledged that large-scale changes are required, particularly in sustainable mobility, where improvement action has to come through policy action, this change will probably have to start at the agent scale (Köhler et al., 2020). Therefore, further model calibration with additional case studies could reveal new scenarios and constraints that have yet to emerge from this initial simulation cycle.

6. Conclusion

In this paper, we developed an ABM of the EV adoption process in a community of individuals. The core of the model is the rate of EV adoption, analysed by integrating in a holistic system view technical, behavioural and external variables and by exploiting calibrating scenarios based on Danieli's (2020), Giansoldati's (2018), and Kowalska-Pyzalska's (2017) research. From a theoretical perspective, we developed an ABM to analyse the complex social system in which individual actors operate by interacting with resources, constraints, and other agents. We built several configurations to study the effect of varying the levels of range anxiety, environmental awareness, and external forces. According to empirical findings, the adoption of EVs exhibits an inverse correlation with range anxiety and a direct correlation with environmental awareness. Additionally, financial incentives and advertising can boost the EV adoption rate, though with diminishing returns, and the combination of these variables at their average levels yields an EV adoption like maximum independent variable scenarios. These initial findings substantiate the model's suitability for simulating the phenomenon of EV adoption. Future research will extend to examining diverse network topologies, including multi-topologies, and scaling up to larger networks with more than 100 agents to enhance our understanding of the dynamics involved. Additionally, the model can be utilised to understand the impact of external events that, although not directly related to the specific topic, can alter the rules and interaction mechanisms of agents. It is imperative to calculate the coefficients for technical, behavioural, and external variables, as their impacts may vary across different geographical contexts. This article provides insights on configuring an ABM to assess variables that affect the adoption of alternative-fuelled cars. The model also provides a flexible framework for future enhancements, such as the integration of new variables and interaction mechanisms, making it adaptable for specific case studies and offering a tool for policymakers and practitioners to encourage the uptake of alternative-fuelled vehicles.

References

Barter, G. E., Tamor, M. A., Manley, D. K., & West, T. H. (2015). Implications of Modeling Range and Infrastructure Barriers to Adoption of Battery Electric Vehicles. *Transportation Research Record: Journal of the Transportation Research Board*, *2502*(1), 80–88. https://doi.org/10.3141/2502-10

Bonabeau, E. (2002). *Agent-based modeling: Methods and techniques for simulating human systems*. www.pnas.orgcgidoi10.1073pnas.082080899

Carley, K. M. (2017). *Validating Computational Models*.

Connolly, D., Mathiesen, B. V., & Ridjan, I. (2014). A comparison between renewable transport fuels that can supplement or replace biofuels in a 100% renewable energy system. *Energy*, *73*, 110–125. https://doi.org/10.1016/j.energy.2014.05.104

Conway, R. W., Johnson, B. M., & Maxwell, W. L. (1959). Some Problems of Digital Systems Simulation. *Management Science*, *6*(1). https://doi.org/10.1287/mnsc.6.1.92

Cozzoni, E., Passavanti, C., Ponsiglione, C., Primario, S., & Rippa, P. (2021). Interorganizational Collaboration in Innovation Networks: An Agent Based Model for Responsible Research and Innovation in Additive Manufacturing. *Sustainability*, *13*(13), 7460. https://doi.org/10.3390/su13137460

Danielis, R., Rotaris, L., Giansoldati, M., & Scorrano, M. (2020). Drivers' preferences for electric cars in Italy. Evidence from a country with limited but growing electric car uptake. *Transportation Research Part A: Policy and Practice*, *137*, 79–94. https://doi.org/10.1016/j.tra.2020.04.004

Dimitropoulos, A., Rietveld, P., & van Ommeren, J. N. (2013). Consumer valuation of changes in driving range: A meta-analysis. *Transportation Research Part A: Policy and Practice*, *55*, 27–45. https://doi.org/10.1016/j.tra.2013.08.001

Dunkin, Ann., ACM Digital Library., & ACM Special Interest Group on Simulation and Modeling. (2009). *Integrating agent-based simulation and system dynamics to support product strategy decision in the automotive industry*. Winter Simulation Conference.

El Sayed, T., Levy, C., Mannion, P., Pacthod, D., Rahi, J., & Sullivan, R. (2023). *Outcomes from COP 28: What next to accelerate climate action?*

Garcia, R., Rummel, P., & Hauser, J. (2007). Validating agent-based marketing models through conjoint analysis. *Journal of Business Research*, *60*(8), 848–857. https://doi.org/10.1016/j.jbusres.2007.02.007

Giansoldati, M., Danielis, R., Rotaris, L., & Scorrano, M. (2018). The role of driving range in consumers' purchasing decision for electric cars in Italy. *Energy*, *165*, 267–274. https://doi.org/10.1016/j.energy.2018.09.095

Gilbert, N., & Terna, P. (2000). How to Build and Use Agent-Based Models in Social Science. In *Mind & Society* (Vol. 1).

Holland, J. H. (1995). How Adaptation Builds Complexity. In *Basic Books*.

Holland-Letz Matthias, Kässer Matthias, KlossThibaut, & Müller Thibaut. (2021). Mobility's future: An investment reality check. *McKinsey&Company*.

Huang, X., Lin, Y., Zhou, F., Lim, M. K., & Chen, S. (2021). Agent-based modelling for market acceptance of electric vehicles: Evidence from China. *Sustainable Production and Consumption*, *28*, 206–217. https://doi.org/10.1016/j.spc.2021.04.007

International Energy Agency. (2021). *Net Zero by 2050 - A Roadmap for the Global Energy Sector*. www.iea.org/t&c/

Köhler, J., Turnheim, B., & Hodson, M. (2020). Low carbon transitions pathways in mobility: Applying the MLP in a combined case study and simulation bridging analysis of passenger transport in the Netherlands. *Technological Forecasting and Social Change*, *151*. https://doi.org/10.1016/j.techfore.2018.06.003

Kowalska-Pyzalska A. (2017). *Willingess to pay for green energy: an agent-based model in NetLogo Platform*.

Krishna, G. (2021). Understanding and identifying barriers to electric vehicle adoption through thematic analysis. *Transportation Research Interdisciplinary Perspectives*, *10*. https://doi.org/10.1016/j.trip.2021.100364

Kumar, R. R., & Alok, K. (2020). Adoption of electric vehicle: A literature review and prospects for sustainability. In *Journal of Cleaner Production* (Vol. 253). Elsevier Ltd. https://doi.org/10.1016/j.jclepro.2019.119911

Maybury, L., Corcoran, P., & Cipcigan, L. (2022). Mathematical modelling of electric vehicle adoption: A systematic literature review. *Transportation Research Part D: Transport and Environment*, *107*, 103278. https://doi.org/10.1016/j.trd.2022.103278

Melliger, M. A., van Vliet, O. P. R., & Liimatainen, H. (2018). Anxiety vs reality – Sufficiency of battery electric vehicle range in Switzerland and Finland. *Transportation Research Part D: Transport and Environment*, *65*, 101–115. https://doi.org/10.1016/j.trd.2018.08.011

Mersky, A. C., Sprei, F., Samaras, C., & Qian, Z. S. (2016). Effectiveness of incentives on electric vehicle adoption in Norway. *Transportation Research Part D: Transport and Environment*, *46*, 56–68. https://doi.org/10.1016/j.trd.2016.03.011

Neshat, N., Kaya, M., & Ghaboulian Zare, S. (2023). Exploratory policy analysis for electric vehicle adoption in European countries: A multi-agent-based modelling approach. *Journal of Cleaner Production*, *414*. https://doi.org/10.1016/j.jclepro.2023.137401

Paris Declaration. (2015). Paris Declaration on Electro-Mobility and Climate Change & Call to Action. *Paris*.

Pillai, A., Curtis, J., & Tovar Reaños, M. A. (2022). Spatial scenarios of potential electric vehicle adopters in Ireland. *Case Studies on Transport Policy*, *10*(1), 93–104. https://doi.org/10.1016/j.cstp.2021.11.008

Ponsiglione, C., Cannavacciuolo, L., Primario, S., Quinto, I., & Zollo, G. (2021). The ambiguity of natural language as resource for organisational design: A computational analysis. *Journal of Business Research*, *129*, 654–665. https://doi.org/10.1016/j.jbusres.2019.11.052

Quak, H., Nesterova, N., & Van Rooijen, T. (2016). Possibilities and Barriers for Using Electric-powered Vehicles in City Logistics Practice. *Transportation Research Procedia*, *12*, 157–169. https://doi.org/10.1016/j.trpro.2016.02.055

Samant, M., Khatri, A., Batra, G., & Goel, A. (2022). *EY Mobility Consumer Index 2022 study - EY Knowledge analysis*.

Scorrano, M., & Danielis, R. (2022). Simulating electric vehicle uptake in Italy in the small-to-medium car segment: A system dynamics/agent-based model parametrised with discrete choice data. *Research in Transportation Business and Management*, *43*. https://doi.org/10.1016/j.rtbm.2021.100736

Silvia, C., & Krause, R. M. (2016). Assessing the impact of policy interventions on the adoption of plug-in electric vehicles: An agent-based model. *Energy Policy*, *96*, 105–118. https://doi.org/10.1016/j.enpol.2016.05.039

Skippon, S. M., Kinnear, N., Lloyd, L., & Stannard, J. (2016). How experience of use influences mass-market drivers' willingness to consider a battery electric vehicle: A randomised controlled trial. *Transportation Research Part A: Policy and Practice*, *92*, 26–42. https://doi.org/10.1016/j.tra.2016.06.034

Smith, B., Olaru, D., Jabeen, F., & Greaves, S. (2017). Electric vehicles adoption: Environmental enthusiast bias in discrete choice models. *Transportation Research Part D: Transport and Environment*, *51*, 290–303. https://doi.org/10.1016/j.trd.2017.01.008

Uncles, M. D., Ben-Akiva, M., & Lerman, S. R. (1987). Discrete Choice Analysis: Theory and Application to Travel Demand. *The Journal of the Operational Research Society*, *38*(4). https://doi.org/10.2307/2582065

Valeri, E., & Danielis, R. (2015). Simulating the market penetration of cars with alternative fuelpowertrain technologies in Italy. *Transport Policy*, *37*, 44–56. https://doi.org/10.1016/j.tranpol.2014.10.003

Van Gogh Margi, Farrag-Thibault Angie, Hausmann Ludwig, Liu Spencer, Mohr Detlev, Weber Benjamin, & Wolff Cristoph. (2022). *Driving decarbonisation: Accelerating zero-emission freight transport*.

Zhuge, C., & Shao, C. (2019). Investigating the factors influencing the uptake of electric vehicles in Beijing, China: Statistical and spatial perspectives. *Journal of Cleaner Production*, *213*, 199–216. https://doi.org/10.1016/j.jclepro.2018.12.099