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An agent-based model for regional market penetration of electric vehicles in Brazil

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ABSTRACT

Electrified vehicle (EV) are increasingly being adopted worldwide, making them promising elements in the decarbonisation process of the automotive sector. However, forecasting EV demand presents a significant challenge for policymakers worldwide. Our study proposes an agent-based simulation model that aggregates the behaviour of individual agents and generates cumulative adoption numbers through the Bass diffusion model. This approach enables using different parameters and extends previous research on actions to improve EV adoption rates in Brazil. Our investigation of the market introduction of EV using a multi-year dataset of EV buyers and marketed vehicle models reveals that acquisition cost is the primary driver of the adoption process. Still, barriers to electric mobility are also associated with vehicle-specific factors such as range, battery capacity, maintenance cost, recharging time, acquisition cost and number of EV sold. These findings emphasise the need to develop more effective policies and strategies for promoting EV adoption in Brazil, considering the factors that affect consumer behaviour and the adoption process. Doing so can accelerate the transition towards a more sustainable transportation system and reduce carbon emissions in the automotive sector.

1. Introduction

Oil dependence and price fluctuations have recently been governing political and research agendas. Replacing fossil fuel combustion vehicles with Electrified vehicle (EV) – which includes hybrid electric vehicles, plug-in hybrid electric vehicles, battery electric vehicles, fully electric, or combining biofuel use – becomes a viable option from both environmental and strategic perspectives (Kangur et al., 2017). For WEF (2021), adopting a rapid transition from the internal combustion engine to EV can be disruptive, especially against the current backdrop of increasing trade barriers and resource nationalism. Thus, the lack of preparedness of countries for a fast-paced technology substitution scenario may increase tension risks in the future. In other words, EV can catalyse further cooperation or represent a source of conflict, implying a deepening of global supply chains, and regulatory and market integration (Gnann et al., 2018).

It is possible to identify several studies aiming to broaden the understanding of EV adoption in several countries worldwide — China (Jian et al., 2018), the United States (Adepetu and Keshav, 2017), South Korea (Li, 2019), Australia (Higgins et al., 2012), Germany (Massiani and Gohs, 2015), Singapore (Zhang and Tay, 2017), Brazil (Brito et al., 2019). Studies on EV adoption in countries like China and the United States seek to understand the needs involved in increasing EV use and meeting CO_2 emission targets. Already in countries like Norway, a world leader in EV adoption, studies have analysed the cultural impacts of EV diffusion (Anfinsen et al., 2019), the effects of battery use (Bauer, 2018) and the public provisioning process (Schulz and Rode, 2022).

Norway is a world leader in EV adoption, with annual rates exceeding 8%. In China, EV sales in 2021 tripled compared to 2020 (3.3 million). In the European market, 2.3 million EV were sold in

Abbreviations: ABM, Agent-based model; ABMS, Agent-Based Modelling and Simulation; ABVE, Brazilian Association of the Electric Vehicle; ANEEL, National Electric Energy Agency; ANFAVEA, National Association of Automotive Vehicle Manufacturers; BEV, Battery Electric Vehicle; DES, Discrete-event simulation; DM, Daily media coverage; DSR, Design Science Research; EV, Electrified vehicle; GIS, Geographic Information System; HEV, Hybrid Electric Vehicle; IEA, International Energy Agency; IBGE, Brazilian Institute of Geography and Statistics; LM, Logistic modelling; MAPE, Mean Absolute Percentage Error; PHEV, Plug-In Hybrid Electric Vehicle; R, Rationality coefficient; RC, Relative costs; RD, Relative desirability; SD, System Dynamics; UML, Unified Modelling Language

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2021, double compared to 2020. In the United States, EV sales already account for 4.5% of vehicles sold in 2021, reaching 630,000 units (IEA, 2023). However, despite efforts to facilitate electrification of the world's transport fleet, EV sales in developing and emerging countries record substantially lower numbers due to higher acquisition costs and a lack of infrastructure (Kumar et al., 2022).

In 2021, Brazil registered 3276 EV, reflecting a 30% growth compared to the previous year. However, when considering the entire Brazilian fleet in circulation – totalling over 46 million vehicles according to the National Association of Motor Vehicle Manufacturers (Anfavea) – the number of registered EV, totalling around 40,000 over the past decade, still needs to be higher (Anfavea, 2023). The challenges faced by Brazil in increasing EV adoption rates include the lack of recharging infrastructure, cost of ownership, tax incidence, and lack of economic incentives and regulations (Anfavea, 2023).

In countries like Brazil, which still face infrastructure problems, encouraging EV adoption without understanding the impacts could lead to a general collapse of the transport and energy structure. Given these challenges, there is an increasing necessity to study EV market share in more detail. EV adoption scenarios in Brazil have been the subject of several previous works. Costa et al. (2021) considered socio-economic and political aspects of assessing the difficulties in adopting EV on the Brazilian territory. Grangeia et al. (2023) analysed hypotheses on the evolution of public policies and EV prices in the country. De Souza et al. (2018) evaluated the environmental impacts of vehicles in the Brazilian context, indicating that EV generate the lowest effects on the environment. Choma and Ugaya (2017) examined how introducing EV may impact the Brazilian environment. Ruoso and Ribeiro (2022) analyses the EV diffusion scenario, identifying barriers that limit its diffusion and possible solutions to overcome them. de Oliveira Gonçalves et al. (2022) provides an impact analysis of three electric, flex and hybrid engine technologies on economic, environmental, social, and infrastructure factors.

Specific studies investigated EV diffusion over time through models that allow analysing different strategies adopted in Brazil to increase EV adoption rates, besides identifying the increase in energy consumption and the impact on alternative sources of traditional fuels in Brazil, such as ethanol and biofuels. These papers used traditional product diffusion models, especially the Bass model, widely used in long-term diffusion studies. In addition, they used System Dynamics (SD) based modelling to incorporate strategic levels of complexity (Benvenutti et al., 2017). Although existing studies have provided valuable information on EV diffusion in Brazil, identifying and modelling new factors and analysing individual consumer behaviour in the adoption process still need to be explored (Grangeia et al., 2023).

However, in the Brazilian EV market, only choices at the strategic level have been considered in the literature. Therefore, the main contribution of the present research is to incorporate the variables of dynamic consumer preferences into a product diffusion model to assess their impact on the market penetration of these vehicles. This is an innovative approach to analysing EV distribution for the Brazilian market.

For this, we propose an agent-based model and simulation (ABMS) to analyse the market penetration of EV in three different scenarios on the Brazilian market, between 2021 and 2035. This study differs from previous efforts in two ways. First, the developed ABMS was used to estimate the spread of potential EV adopters as agents interacting together through factors related to imitation and innovation coefficients. Secondly, we adapted a traditional model in product diffusion (Bass model) to consider new factors: range, battery capacity, maintenance cost, recharging time, acquisition cost and number of EV sold.

The remainder of this paper is organised as follows. Section 2 provides a state-of-the-art review of consumer preference modelling in EV diffusion and forecasting studies. Section 3 introduces the methodology. The ABMS model developed for this study is described in Section 4. Section 5 presents the results, and a discussion is reported in Section 6. Finally, Section 7 concludes the paper and suggests future research.

2. Literature review

This background literature review covers the factors influencing the EV adoption process (see Section 2.1) and the diffusion and forecasting models applied to the EV market (see Sections 2.2 and 2.3).

2.1. Factors in EV adoption

For Asadi et al. (2021), studies examining the factors influencing EV adoption from a consumer perspective have gained relevance. In order to categorise the factors, Singh et al. (2020) proposes a split into 4 groups: demographic, situational, contextual, and psychological. The demographic characteristics deal with general consumer identifiers (e.g., household income, household composition, age, marital status). The situational factors deal with the environment (availability of natural resources, climate change), technological resources (range, type of maintenance, charging time, brand), financial data (acquisition cost, charging cost, operational costs), and market effectiveness. The contextual factors are derived from government policies (purchase tax reduction or exemption) and charging infrastructure. The psychological factors personalises the consumer regarding attitudes (EV riding experience), perceived behavioural control (battery life), and social influence (Singh et al., 2020).

In general, EV adoption is influenced at multiple levels by several types of factors. Gnann et al. (2018) proposes that in addition to psychological factors, such as environmental awareness and innovative personality, operating and maintenance costs are among the main drivers in the EV procurement process in developing countries. This perception is similar to that identified in Rezvani et al. (2018), who highlights that acquisition costs, and individual and social habits modify EV consumption patterns. Neves et al. (2019) underlines influence factors such as vehicle safety, comfort, maximum speed, battery range, long charging times, and the environmental impact of battery disposal as differentials in the acquisition process. For Singh et al. (2020), situational and contextual factors mostly depend on consumers' willingness to purchase EV. Primarily, the analysis of these factors is based on the introduction of dependent variables such as battery capacity (Zhang et al., 2018), range and price (Krause et al., 2016), maintenance costs (Wang et al., 2018), charging infrastructure and time availability (Higueras-Castillo et al., 2021), and potential market size in both mature markets (Yang et al., 2023) and developing economies (Goel et al., 2023). From that, because there is already a solid knowledge base on the insertion of dependent variables regarding situational and contextual factors, we chose to adopt them in the development of the proposed ABMS model.

2.2. New product diffusion theory

The diffusion of innovations theory has long been used to study the adoption of new products. This theory models the impact of various factors, such as the ones presented in the previous section, on adopting new technologies or products and describes current and potential adopter behaviour (Gnann et al., 2018). The diffusion of new product modelling has been a topic of practical and academic interest since the 1960s (Bass, 1969). Since the initial studies, modifications were required to give flexibility to the models, broadening the understanding of the factors that may influence the process of new product adoption, including alterations in the parameterisations of marketing variables, applying predictive pre-models for product sales behaviour and technology adoption in successive generations. Van Oorschot et al. (2018).

The diffusion of new product analysis based on individual consumer decisions is called the consumer choice method (Ayyadi and Maaroufi, 2018). For Meade and Islam (2006), market diffusion factors are estimated in consumer choice methods with multinomial models or utility functions, among the most prominent diffusion models in the literature is the Bass model, which has been extended and modified to incorporate different variables and improve its predictive power.

The original Bass diffusion model is an aggregate diffusion model that uses individual-level characteristics to define the predictive behaviour of new technology adoption (Meade and Islam, 2006). The Bass model is based on the assumption that the probability of purchase at any given time is linearly related to the number of previous buyers in a contagious process driven by external influence (advertising) defined as parameter p, and internal impact defined as q (word-of-mouth) (Bass, 1969). The number of purchases n_t at time t is expressed according to Eq. (1):

$$n_t = \frac{dN_t}{dt} = p + q \times \left(\frac{S_t}{m}\right) \tag{1}$$

where n_t is the number of product purchases in period t; N_t is the cumulative product purchases up to the beginning of period t; p is the innovation coefficient; q is the imitation coefficient; S_t is the total cumulative number of consumers; t is the time of purchase; and m is the market potential over the entire product life cycle.

The Bass model equation is fitted using existing sales data, as per Eq. (2):

$$F_t = \frac{1 - e^{-(p+q)\times t}}{\left(1 + \frac{q}{p}\right) \times e^{-(p+q)\times t}} \tag{2}$$

where F_t is the cumulative fraction of the potential reached in time t (market penetration).

The fraction of the available market that will adopt a product at time t is defined according to Eq. (3):

$$f_t = [p + (q \times F_t)] \times [1 - F_t] \tag{3}$$

where f_t is the sales density function at time t.

The growth rate of the number of new consumers is represented in Eq. (4):

$$h_t = \left(\frac{1}{M - S_t}\right) \times \left(\frac{dS_t}{dt}\right) \tag{4}$$

where h_t is the growth rate of new consumers; M is the market potential accumulated over the product's entire life cycle.

Applying these equations will result in an S-shaped yield curve, representing the cumulative proportion of the population adopting the innovation (Bass, 1969).

The diffusion pattern depends on an estimate of the potential market and the values of p and q. In the Bass model, parameters p and q are calibrated with sales data for the market and provided by the literature or by parameter estimates based on actual data (Massiani and Gohs, 2015). Beyond product diffusion models, modelling and simulation have been increasingly adopted to understand the new product adoption process. They operate individually and can capture complex emergent phenomena highly relevant in new product diffusion research (Kumar et al., 2022).

Among different modelling and simulation methods used to understand new product adoption behaviour, ABMS can capture complex dynamic behaviours that emerge from autonomous and heterogeneous agents belonging to the system (Eppstein et al., 2011). These agents act from features and rules in search of collective responses, such as adopting a new product (Noori and Tatari, 2016). ABMS is a category of computational models based on dynamic actions, reactions, and intercommunication protocols between agents in a shared environment to evaluate performance, behaviour, and emergent properties (de Paula Ferreira et al., 2022b). The function of an individual component can range from basic if-then reactive rules to complex behavioural models (de Paula Ferreira et al., 2020).

ABMS allows modelling diffusion processes where consumer agents decide according to a simple weighted utility of individual preference and social influence, and where consumers weigh factors such as price, fuel consumption, model, acceleration, and safety to determine which vehicle to purchase (Oliveira et al., 2019). This makes it possible to calculate adoption indicators considering these factors concerning the influence of mass media and the word-of-mouth effect at the macro level (potential market) and the micro level (agent behaviour) for the analysis of the EV adoption scenario (Ayyadi and Maaroufi, 2018).

An agent-based model (ABM) is composed of agents that interact with each other to extend the understanding of a system's behaviour and what governs its potential emergent behaviour outcome (Macal and North, 2010). The main components of an ABM are the agents, the environment in which they act, the rules that govern the agents' communication, behaviour, and decision-making functions, and the interactions with each other and their environment (de Paula Ferreira et al., 2022a). Agents are the most significant elements in ABM. They are autonomous, independent, and proactive and can initiate actions without necessarily being triggered by an external mechanism (Zhang et al., 2020). Moreover, they are adaptable, with learning skills that can gradually improve after their interactions and subsequently influence their behaviour and decision-making attributes (Eppstein et al., 2011). ABMS has distinctive features that confer uniqueness and benefits over frequently used simulation techniques, such as discrete event simulation (de Assis et al., 2021). The following subsection outlines previous studies that use diffusion theory, and ABMS applied in the EV market.

2.3. Diffusion models applied in the EV market

Brusch et al. (2015) proposed that the Bass model, in general, makes it possible to adjust parameters efficiently compared to other forecasting models and that because of this characteristic, it is one of the most widely used models for diffusion estimation purposes. Eppstein et al. (2011) formulated a hybrid model using ABM and trend fitting, in which media coverage and social interactions over time affect a potential consumer's purchase decision. Cagliano et al. (2017) proposed the Bass model in three interconnected parts. The first part represents the dynamics of the Bass model. The second determines the number of EV needed as a function of the number of adopters. Lastly, the third part includes the adoption parameters needed for scenario generation. In Higgins et al. (2012), the complexity arising from consumers' decisions to purchase EV was studied through multi-criterion analysis, and the Bass model was used to estimate adoption. In Li (2019), EV adoption is affected by messages communicated in mass media and the feedback that current users give to future users. Using the Chinese EV market as an example, the function n_t represents the number of newly added EV at time t, where a is an "innovative" coefficient (external factor), and b represents an "imitative" coefficient (internal factor). The probability of individuals obtaining information on EV is a constant, defined as the information diffusion speed. It is assumed that information dissemination starts before EV commercialisation. The average probability of acceptance is modelled by a factor reflecting the number of people who have already adopted EV and a constant used to model imitation over time (Zhang et al., 2020).

Kieckhäfer et al. (2014) uses a hybrid simulation approach to estimate the evolution of EV market share by integrating an SD model with ABM from the Bass model parameters. Consumer choice, consumer awareness, evolving technology, and station availability are examined in the SD. ABMS addresses the interaction between macro-level and heterogeneous consumer behaviour in refining the consumer choice and awareness model. Also using SD (Neumann et al., 2014) introduced a simulation-based forecasting approach combining concepts from the Bass Diffusion Model and the Discrete Choice Model, parameterised through a joint analysis and using individual preferences and social forces to predict adoption rates — the study suggests battery charging infrastructure and technology are critical to electric car success in Germany.

Eggers and Eggers (2011) developed and tested a choice-based joint adoption model that uses individual-level preferences as the basis for prediction. In Fan and Zhang (2018), the forecast was based on a regression model from the analysis of user trip data and an expectation of the average daily mileage of EV. In Shafiei et al. (2012), from an ABMS the market share of different vehicles over the period 2012–2030 is obtained using fuel prices, vehicle taxes, the future price of EV, and charging concerns on market share, which are analysed with the help of the model as input parameters, using a strategy in which consumers who do or do not adopt EV are defined using a consumer choice algorithm. Kangur et al. (2017) states that in a diffusion process with technological and financial developments and a possible change in the social context, non-linear consequences can occur, exploring this behaviour from the parameterisation of an agent architecture capable of simulating different consumer needs and decision strategies. Gschwendtner et al. (2023) developed an agent-based model to investigate how different charging system behaviours affect EV diffusion and infrastructure charging. Noori and Tatari (2016) addressed uncertainties inherent in the market share of EV in the United States using an ABM that considers vehicle attributes for different types of vehicles to identify their market shares.

According to de Rubens (2019), regardless of geography, it is possible to identify those early adopters as middle to high-income individuals, usually male, with undergraduate or postgraduate degrees, who may be technologically and environmentally engaged, regardless of geographic location, as found in a study conducted in Austria (Gass et al., 2014), Canada (Axsen et al., 2016), Germany (Lieven et al., 2011), the United States (Hardman et al., 2018), and Sweden (Vassileva and Campillo, 2017). Sgouridis et al. (2018), highlighted the impact of opportunity costs and environmental externalities on purchasing a new EV in Abu Dhabi. Xiong et al. (2023) proposes a random logit coefficient model to quantitatively analyse EV consumer preferences in China, emphasising regional disparity and different operational purposes.

In a different approach, Dhakal et al. (2021) used Bass' model in a standard format coupled with logistic modelling (LM) using historical EV sales data to predict purchasing behaviour in the European Union, highlighting the adaptability feature in both models. Massiani and Gohs (2015) proposed that the description of basic parameters occurs in two ways: (i) provided by the literature; (ii) parameter estimates based on accurate data. Lee et al. (2019) uses social classes from a demographic study as input factors in the Bass diffusion models to identify the socio-economic profile of future EV adopters in California. Jian et al. (2018) used cost to calculate savings between power generation technologies, from how much it costs to drive a vehicle per kilometre over the vehicle's lifetime.

2.4. Review of EV diffusion models in Brazil

Complementary to the previous section, herein we review previous studies on EV diffusion models for the Brazilian market. Baran and Legey (2013) pioneered work with SD-based simulation models and a Bass model in measuring the impact of EV on the Brazilian market energy consumption through diffusion models, demonstrating how electricity could complement ethanol and gasoline. Benvenutti et al. (2017), also using the SD and Bass model combination, investigated the long-term impact of public policies on the diffusion process of EV. Brito et al. (2019) based on the multi-generation diffusion model and on the traditional Bass model, predicted the market potential for EV adoption compared to traditional technologies (ethanol and biofuel) in Brazil. Rodrigues et al. (2019) presented a space–time model using a geographic information system, which estimates the adoption rate of electric vehicles by sub-areas, identifying the regions with the highest probability of adopting EV. A study conducted by Brito et al. (2020) examined the impact of gasoline and alcohol price elasticity on the market share of different types of vehicles. Bitencourt et al. (2021) developed a simulation model to test policy strategies adopted in Brazil to increase EV adoption rates, adapting the Bass model to conclude that the high EV prices may still be the main barrier to EV diffusion in Brazil over the studied horizon, keeping them unaffordable for most of the population. Schmidt et al. (2022) implements the Bass model to demonstrate the impact of EV charging operations and energy consumption segmented by fleet type through 2030. Grangeia et al. (2023) uses a definition of technical, economic and fiscal parameters to assess the evolution of public policies and EV prices in the country, using the Bass model and SD modelling.

In summary, current research on Brazilian consumers' EV preferences has directed attention to SD-based modelling and uses the Bass model (see Table 1). This is because SD tends to incorporate structures at the level of social phenomena such as word of mouth, commonly presented as differential equations, and the time horizon tends to be related to long-term forecasting (Bitencourt et al., 2021). Such factors bring the Bass model closer to SD and make it easier to adapt to stock and flow notation (Benvenutti et al., 2017). However, making plausible predictions about future consumer behaviour remains challenging, even when equipped with strategic information (Grangeia et al., 2023). Technological and infrastructural developments depend on different market participants, causing uncertainties regarding charging times, charging speeds, charging locations, maximum range and fuel prices (Brito et al., 2020).

We investigated this gap by developing an ABM based on the Bass model, adapted to take into account the relationship between aggregate factors – innovation and imitation coefficients, number of EV sold, and population growth projections – with the following specific factors: autonomy, battery capacity, maintenance cost, recharging time, acquisition cost. Acquisition costs, battery capacity, and autonomy are among the most commonly used factors in studies on increasing the market share of EV (Jian et al., 2018). Maintenance cost is a prominent factor, as one of the most impactful operating costs in EV decision-making (Rezvani et al., 2018). As well as, the charging time can influence the adoption process (Coffman et al., 2017). Such studies supported the ABMS proposed in this paper. Consequently, our research on the impact of these factors on EV adoption in Brazil will allow us to understand the impact of heterogeneous consumer behaviour on the evolution of EV market share and vice versa.

3. Methodology

Simulation modelling is a key research methodology used for other purposes such as discovery, explanation, critique, proof, prediction, prescription, and practical guidance (de Paula Ferreira et al., 2022b). Some popular simulation modelling methods include discrete-event simulation (DES), SD, ABMS, and hybrid simulation (Furlan de Assis et al., 2023). This study adopts the ABMS method, which offers a way to model complex systems (e.g. social systems) by stochastically simulating behaviours and interactions of heterogeneous autonomous agents (Macal and North, 2010). ABMS is a decentralised approach consisting of software agents with different levels of autonomy "that represent physical or logical objects in the system, capable of acting to achieve its goals, and being able to interact with other agents, when it does not possess knowledge and skills to reach its objectives alone" (Leitão, 2009).

This study uses the design science research (DSR) paradigm as the theoretical basis for the methodological component. It presents a set of procedures in conceptualising, developing, testing, and validating artefacts, including tools, methods, and models like the one described in this paper (Marques et al., 2021). By designing and evaluating artefacts, design science aims to provide innovative or more efficient solutions to problems in the real world (Peffers et al., 2007). In this case, the artefact is the proposed model that addresses the problem of EV diffusion in Brazil to further the understanding of the factors that influence this process.

ABMS development involves three typical phases: design, implementation and analysis (Scheidegger et al., 2018). In this study's design

Table 1
Diffusion models and factor categories on EV diffusion in Brazil.

Diffusion model	Modelling method	Factor category				Main contribution	Reference
		(1)	(2)	(3)	(4)		
Bass model	SD	✓				Measure the impact on energy consumption with introduction EV	Baran and Legey (2013)
	SD			✓		Investigate the impact of government policies on the diffusion of EV	Benvenutti et al. (2017)
	SD			✓		Analyse factors that drive electric mobility in Brazil	Grangeia et al. (2023)
	Discrete-time		✓			Understand the evolution of a successive generation of vehicle technologies	Brito et al. (2019)
	Econometric			✓		Evaluate the impact of public policies on EV diffusion in Brazil until 2050	Bitencourt et al. (2021)
	Discrete-time			✓		Forecast the number of EV and energy consumption up to 2030	Schmidt et al. (2022)
Space–time	GIS		✓			Estimate the adoption rate of electric vehicles by area	Rodrigues et al. (2019)
Market-share	Econometric	✓				Estimate the fuel price elasticity of the EV market share	Brito et al. (2020)
Bass model	ABM		✓	✓		Investigate the influence of acquisition cost, battery capacity, maintenance cost, autonomy and recharging time on the EV adoption process	This Study

Legends: (1) — Demographic; (2) — Situational; (3) — Contextual; (4) Psycological; SD — System Dynamics; GIS — Geographic Information System; ABM — Agent-based modelling.

Table 2
Types of vehicles used.
Source: Adapted from Manufacturers' website.

Vehicle	General features		
	Model	Technologies	Body shape
Model A	Nissan Leaf Tekna	BEV	Hatchback
Model B	Porsche Taycan	PHEV	SUV
Model C	Volvo XC40 Recharge	BEV	SUV
Model D	Mini Cooper Electric	BEV	Hatchback
Model E	Audi e-Tron	PHEV	SUV
Model F	BMW i3 BEV 120AH	BEV	Hatchback
Model G	Fiat 500e Icon	BEV	Hatchback
Model H	Chevrolet Bolt	BEV/HEV	SUV

Legend: BEV — Battery Electric Vehicle; HEV — Hybrid Electric Vehicle; PHEV — Plug-In Hybrid Electric Vehicle.

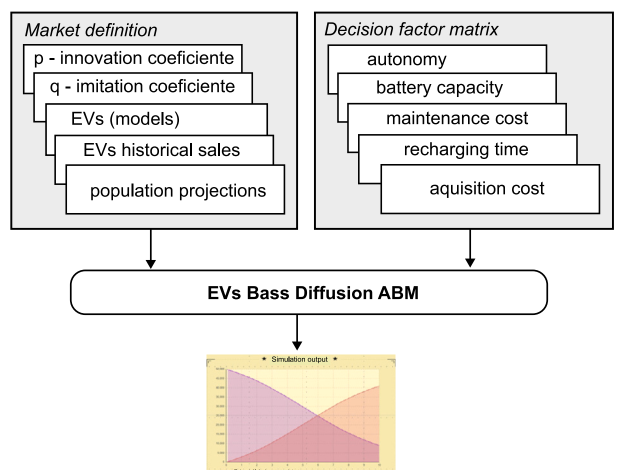


Fig. 1. EV factors and Bass Diffusion Agent-Based Model (ABM).

phase, we adopted flowcharts mainly as modelling tools. In the implementation phase, we adopted AnyLogic software, a leading commercial multi-method simulation modelling tool available on the market, which supports DES, SD and ABMS and has features including a moderate level of effort in model design and development, high computational modelling power and model scalability (Abar et al., 2017). The simulation model's output was analysed using Python programming in the analysis phase. The following sections provide more details on the development methodology of the proposed ABMS.

4. Proposed agent-based model

The proposed ABMS was developed based on the consumer as an agent. As part of the simulation, the ABM estimates the adoption rates of heterogeneous agents (consumers) for each vehicle during the simulation period based on autonomy, battery capacity, maintenance costs, charging times, and acquisition costs. The ABMS results represent the input data for total product purchases in the period to estimate the adoption curves of the Bass model. Fig. 1 represents the developed ABM.

To control EV adoption factors, we chose to model potential new car buyers (agents) who restricted their choices to 8 types of EV (Table 2) with different characteristics in terms of autonomy, battery capacity, maintenance cost, recharging time, and acquisition cost. Differences in factors can affect rational financial considerations – an agent receives a sensible estimate of the acquisition cost – and other heuristic considerations – financially irrational calculations of fuel economy or the desire to reduce gas emissions – related to vehicle choice. The EV selected correspond to the eight best-selling cars in 2021.

We defined a random distribution that took into account annual salary values above R$ 90,000.00 to make sure that the salaries of all agents were sufficient to pay for at least one of the vehicles in question. Such salary distribution was an assumption in the agent definition flow. While infrastructure and government policy may be dominant factors in some regions or countries, the dynamics of electric car adoption can vary greatly depending on the context (Noori and Tatari, 2016). Brazil, for example, may have unique socio-economic conditions, consumer preferences, and market dynamics that require considering salary and relative cost as crucial factors in predicting the adoption curve of EV (Grangeia et al., 2023). In addition, we included a spatial neighbourhood, a market share threshold over which they are willing to adopt EV, and a rationality coefficient (R) that establishes rational or irrational contact with the factors. The agent's attribute G initially weights the perceived benefits related to the acquisition costs.

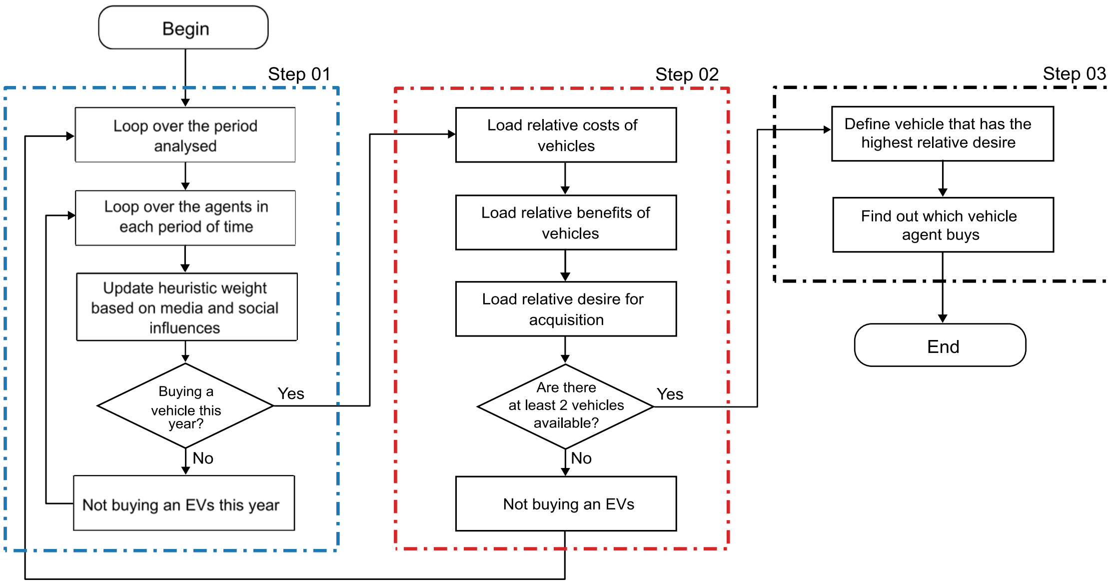


Fig. 2. Flowchart of annual updates of the agents' vehicles (Purchasing Algorithm).

The agent is updated asynchronously in every simulated period, per the flowchart in Fig. 2.

In step 01, the agent's value for the heuristic weight G changes according to media and/or social influences, where agents are exposed to a random distribution of daily media coverage (DM) up to the period when each agent considers buying a car. The intensity of media coverage is a time series of real numbers between 0 and 1.

For Oliveira et al. (2019), changes in media coverage can influence attitudes over time, which allows adjusting each consumer's G-weight by considering the difference between the agent's innovation coefficient and imitation coefficient, according to Eq. (5):

$$G_t = G_{(t-1)} + [DM \times (p - q) \times R] \tag{5}$$

where G_t is the weight for the consumer; $G_{(t-1)}$ is the previous consumer's G weight; DM is the media coverage; R is the rationality coefficient, where 0 indicates irrational purchase and 1 rational purchase.

In step 02, the agent considers the purchase of a new vehicle during the current year subject to a normal probability distribution based on the standard adoption number for the analysed period. Agents are willing to consider purchasing a vehicle to estimate relative costs of all viewed vehicles (RC). According to Oliveira et al. (2019), agents estimate the cost of each car (C) as per Eq. (6):

$$C_t = (C_B + C_M + C_R) \times R \tag{6}$$

where C_t is the cost of the new vehicle; C_B is the lower purchase price; C_M is the net present value of the first revision; C_R is the battery recharging cost.

In estimating projected relative costs, agents receiving $R = 0$ do not reasonably estimate projected fuel costs. Those with $R = 1$ calculate the fees over specific years, and recharge cost is defined according to Eq. (7):

$$C_R = \int_B^0 (C_{EP} \times BC)dt \tag{7}$$

where BC is the battery capacity established for each type of vehicle; C_{EP} is the cost of electricity at time t in (R\$/KWh).

If the selected agent receives $R = 0$, the total cost is not computed as a selection factor, and a random function establishes the buying process. Eq. (7) represents the product between electrical cost and energy capacity of the vehicle battery (i). Electrical costs started from R\$ 0.38217 (R\$/kWh), based on the average price of 2021 and a linear increase of 0.27% per year over 25 years, as suggested by the National Electric Energy Agency (Aneel, 2022). For the maintenance cost factor, we adopted the value of the first revision as per the manufacturers' website.

According to Oliveira et al. (2019), the relative perceived peer costs of all vehicles i and j are estimated according to Eq. (8). Vehicle i is the one with the lowest C_B, defined from a comparison between pairs of cars:

$$CTotal_{ij} = min\left(\frac{C_j - C_i}{C_j}\right) \tag{8}$$

where C_i is the cost of car i for each ordered pair created and C_j is the cost of car j for each ordered pair created.

According to Jian et al. (2018), the relative benefits (RB) to pairs (F_{ij}) of each factor i are heuristically estimated for all vehicles j considered for each generated agent, comparing the relative difference for each element, as per Eq. (9):

$$RB_{ij} = max\left(\frac{F_j - F_i}{F_j}\right) \tag{9}$$

where F_i is the relative benefit for car i and F_j is the relative benefit for car i.

As per (Eppstein et al., 2011), the relative desirability (RD) to all pairs of vehicles is calculated by weighing the estimated relative costs and benefits according to the current weight value of agent G, as per Eq. (10):

$$RD_{ij} = (G \times (1 + CTotal_{ij})) + (G \times RB_{ij}) \tag{10}$$

where RD_{ij} is the relative desired benefit for a car.

If $RD_{ij} \geq 0$ vehicle j is considered the more desirable of the two vehicles. The values of RD_{ij} may change if a car's estimated maximum maintenance cost exceeds a constant 20% of the agent's salary. If $RD_{ij} = 0$, the vehicle is not accessible. In this case, the agent's threshold is greater than the proportion of EV owned by the agents (we define that each agent has a maximum of 2 EV).

If at least one vehicle is considered affordable, in step 03, the agent evaluates all paired comparisons of the relative desirability of the RD vehicle and purchases the most desirable vehicle. The total product purchases in period t are defined according to Eq. (11):

$$n_t = \left(\frac{dRD_{ij}}{dt}\right) \tag{11}$$

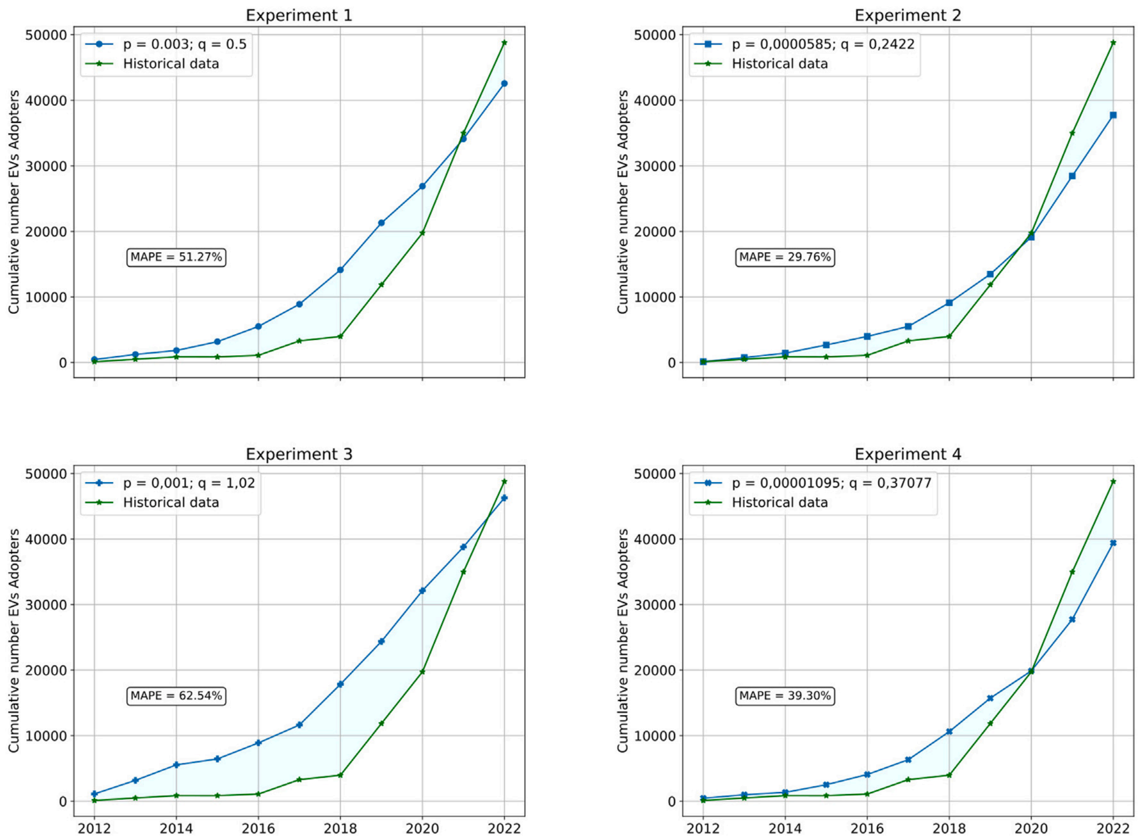


Fig. 3. Results of the number of adopters in the experiments performed for verification. *Legend:* p — innovation coefficient; q — imitation coefficient; n — number of agents.

where n_t is the total EV purchases in period t and RD_{ij} is the relative desired benefit for a car.

The total purchase is an input parameter of the Bass model to obtain the cumulative fraction of potential (N_t), according to Eq. (12):

$$N_t = N_{t-1} + [p \times (m - n_{t-1})] + [q \times (m - n_{t-1})] \tag{12}$$

where N_t is the cumulative fraction of EV potential market in t period; N_{t-1} is the cumulative fraction of EV potential market in the last period; and n_{t-1} is the total product purchases in the last period.

If the agent decides to buy a vehicle, the vehicle attributes are loaded, and the agent's preferences are accounted for. Then, we calculate the cumulative fraction of adoption potential (F_t), sales density function (f_t), and the cumulative total of adopters (S_t). The type of vehicle the agent finally buys is determined along with the growth rate of the number of new consumers (h).

The cumulative market potential M_t over the simulated period is defined according to Eq. (13):

$$M_t = \sum_{i=1}^{m} N_t \tag{13}$$

where M_t is the cumulative market potential and N_t is the cumulative fraction of the potential EV market.

The following subsection presents the input data collected to implement the ABM for simulation purposes.

4.1. Data collection

For preliminary data composition, the historical series on vehicle licensing was made available by Anfavea (2023). We considered light commercial vehicle sales from 2012 to 2021, as shown in Table 3.

For Jaiswal et al. (2021), emerging market data can be difficult to work with due to significant data gaps, outdated or incorrect.

Table 3
List of licensed vehicles per year.
Source: Adapted from Anfavea (2023).

Years	Vehicle refuelling methods			
	Gasoline	EV	Flex Fuel	Diesel
2012	273,915	117	3,162,874	197,277
2013	189,109	491	3,169,114	221,182
2014	184,841	855	2,940,508	207,279
2015	136,150	846	2,194,020	149,516
2016	80,495	1091	1,750,748	156,262
2017	68,902	3296	1,927,221	176,565
2018	81,935	3970	2,168,173	221,260
2019	73,853	11,858	2,328,650	251,222
2020	58,930	19,745	1,664,999	211,154
2021	53,587	34,990	1,624,348	264,185
2022	48,804	49,262	1,633,282	229,114

Therefore, the database provided in Anfavea (2023) was analysed and considered because the availability of quality data can be a significant limitation in modelling. Vehicle definitions and the dataset was provided by Anfavea, the Brazilian entity that includes manufacturers of cars, light commercials, trucks, buses, and agricultural and construction machinery. Anfavea's objective is to study industry issues, promote debates, produce studies, compile data and disclose the performance of its automotive sector in Brazil, in addition to coordinating and defending the collective interests of its member companies.

For calculation purposes, we considered the recharge time related to the battery at maximum charge and the autonomy equivalent to the mileage run at maximum battery capacity. The data used are available on the manufacturers' websites and at the Brazilian Association of the Electric Vehicle (ABVE), a civil association of private non-profit law which prioritises the performance with the authorities and business entities linked to the automotive sector, aiming at making decisions that encourage the development and use of EV (ABVE, 2023).

Table 4
Values of the influence factors by type of EV.
Source: Adapted from the manufacturer's website and ABVE (2023).

EV model	Influence factors				
	Acquisition cost (R$)	Maint. cost (R$)	Battery capacity (kWh)	Autonomy (km)	Recharging time (h)
A	298,490	3050	40.00	378	12.00
B	695,000	9800	79.20	504	9.00
C	417,000	2799	78.00	418	8.00
D	257,990	1480	32.60	260	7.30
E	609,990	1734	95.00	446	9.00
F	340,950	1000	42.20	350	8.00
G	224,990	550	42.00	312	7.00
H	279,990	664	60.00	416	10.00

Table 5
Parameters for ABM verification and validation.

Parameter	Experiments			
	1	2	3	4
p	0.003	0.0000585	0.001	0,00001095
q	0.5	0,2422	1,02	0.37077

Legend: p — innovation coefficient; q — imitation coefficient.

It is worth noting the growth in EV registered in 2019. This growth causes an acceleration in operational needs related to maintenance costs and charging infrastructure (ABVE, 2023). For the composition of influence factors, we used the 8 best-selling light EV models in Brazil in 2021, as shown in Table 4. The relative acquisition cost was fundamental in generating agents in ABM and interpreting the results, because this factor is still the main driver in developing country markets (Grangeia et al., 2023). Issues of infrastructure availability and government policies have already been addressed in previous works, which served as a reference for the development of the models proposed in our research, in addition to providing data for the construction and simulation of the proposed scenarios.

4.2. Model verification and validation

The computational model was verified by researchers and validated through a combination of techniques. The first technique consisted in degenerate tests, which involved testing the model's behaviour by selecting appropriate input values and internal parameters (Sargent, 2013). To build the tests, we used the values proposed in Baran and Legey (2013) for Experiment 1, Benvenutti et al. (2017) Experiment 2, Brito et al. (2019) Experiment 3 and Schmidt et al. (2022) Experiment 4. Specifically, these four values proposed in previous studies on EV adoption rates in the Brazilian market were used (see Table 5).

The objective of this validation stage was to identify how changes in different parameters of the Bass model affect the adoption rates when compared to the historical curves of EV in Brazil from 2012 to 2022. Fig. 3 indicates variations in the adoption curves from parameter changes considering a cumulative number of EV adopters. In addition, Fig. 3 presents the mean absolute percentage error (MAPE). MAPE provides a normalised error, allowing a comparison of the efficiency of different models from different datasets, as presented in Eq. (14):

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{Y_i - \hat{Y}_i}{Y_i}\right| \times 100\% \tag{14}$$

where n represents the number of data points, Y_i represents the actual values and $\hat{Y}_i$ represents the predicted values.

The results of Experiment 2 show that the adoption curve achieved the lowest MAPE compared to other experiments. This suggests that lower values of the imitation coefficients used in the experiment are better aligned with the adoption curve than the historical data of the Brazilian EV market.

Using ABM brought the need to evaluate one or more external variables of the diffusion process. To this end, the second technique used to validate the data was a sensitivity analysis, which consists in changing the values of the input and internal parameters of a model to determine the effect on model behaviour or output (Sargent, 2013). In this study, we evaluated the sensitivity analysis of the model to the acquisition cost, as it presents the most significant variations compared to the other factors proposed in this research. Based on the parameters of Experiment 2, we selected values that represent a range of scenarios for the additional acquisition cost of EV in Brazil. Fig. 4 shows the adoption curves. The form of representation of the adoption results occurs through the S-curve in which the horizontal axis is a time scale measure. The vertical axis results from the number of cumulative adopters up to a limit of 50,000 agents. The sensitivity analysis was designed to explore the potential effects of variations in these values on the simulation model results. These specific values create a meaningful range for the sensitivity analysis.

5. Results

For the simulation of the developed model, scenarios were proposed and defined according to the (Anfavea, 2023) report "The Road to Decarbonisation of the Automotive Sector", which addresses the decarbonisation process of the vehicle fleet in Brazil, presenting efforts to reduce greenhouse gas emissions found on the agenda of the global automotive industry and by which Brazil needs to adjust its infrastructure in order to integrate with this reality. According to this report, depending on the scenario, EV will represent 12% to 22% of the sales mix in 2030 in the country and 32% to 62% in 2035. The ABMS results will be obtained from the three scenarios (see Table 6).

According to Anfavea (2023), in the inertial scenario, combustion engines maintain rates of 85% to 90% of the total number of licenses in the next 15 years. EV are targeted to meet specific segments, emission requirements, and corporate consumer demands, leading to a low level of electrification in the higher volume segments. In the global convergence scenario, the technological evolution and the increasing pace of adoption allow EV to gain ground in Brazil, reaching 2035 penetration levels by segment similar to Europe in 2030. Brazil approaches the electrification levels of developed markets as manufacturers follow global electrification strategies, and new markets emerge due to high adoption rates (Anfavea, 2023).

Table 6 presents the parameters used to simulate the proposed scenarios. For the biofuel protagonism scenario, ethanol gains protagonism as a viable alternative for decarbonisation, made possible by favourable regulation for the flex fleet and expansion of production infrastructure, facilitation in distribution, and tax reduction.

Structuring the scenario data for the simulation was based on the EV licensing figures from 2012 to 2021 to simulate the behaviour of adoption rates from 2021 to 2035. Estimating parameters related to the Bass model – such as the innovation and imitation coefficients or the potential market size – can be challenging due to the relatively low adoption stages for which limited data may be available for an accurate

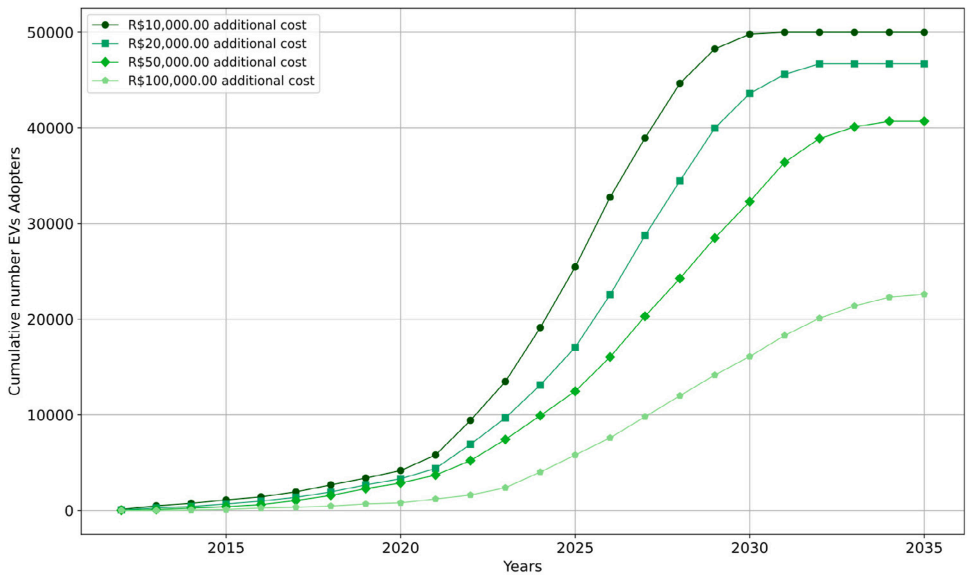


Fig. 4. Results of the number of adopters in the sensitivity analysis.

Table 6
ABM and Bass model parameters for the simulated scenarios.

Parameter	Scenarios		
	Inertial	Global convergence	Biofuel protagonism
p	0.00030	0.00050	0.00015
q	0.40	0.60	0.35
n	50000	50000	50000
Contact Rate	100	200	50
EV threshold	2	4	2

Scenarios: Inertial — adoption rates follow the current pace with no targets set; Global convergence — acceleration in adoption rates follows the movements already underway in more developed countries; Biofuel protagonism — privileges for biofuels with similar "Inertial" scenario strategies. *Parameters:* p — innovation coefficient; q — imitation coefficient; n — number of agents.

statistical estimation of these parameters (Massiani and Gohs, 2015). In this case, previous research on EV diffusion in Brazil generally used estimates from previous literature or car manufacturers as a common practice to address this challenge (Grangeia et al., 2023).

Thus, the p and q parameters adopted in the inertial scenario follow those proposed in Massiani and Gohs (2015). In the global convergence scenario, p and q were adopted as suggested by Lee et al. (2019) following EV adoption patterns in the United States. For the biofuel protagonism scenario, we used the p and q parameters according to Bitencourt et al. (2021), which analysed the expansion of hybrid systems among flex-fuel vehicles in Brazil. However, a critical point can be highlighted as there might be something different in demand from one country compared to another, making it necessary to adjust the imitation and innovation factor, for which we suggest further research activities on the performance of Bass models based on the transferred parameter values (Massiani and Gohs, 2015).

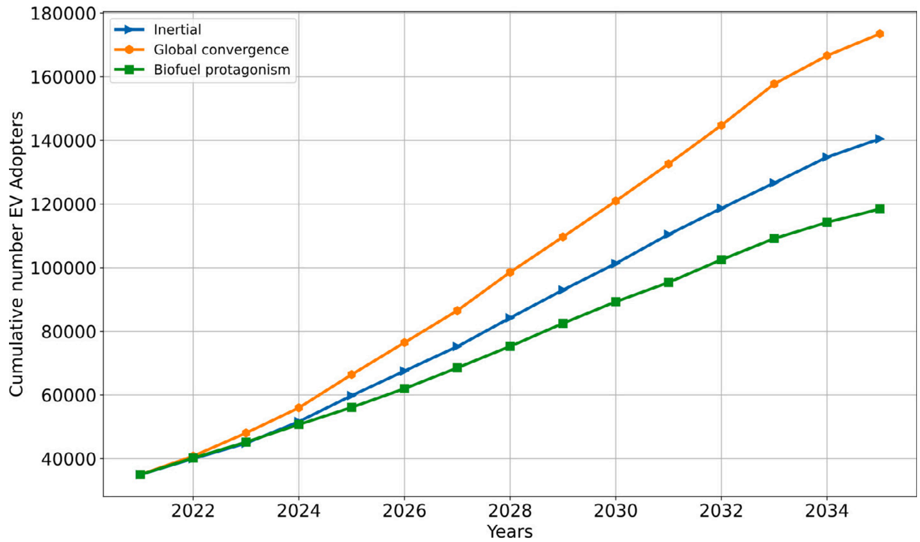
We defined the existence of 34,990 agents as a cumulative number of EV registered in Brazil by 2021, with a contact rate of 100% to show that each generated agent influences another agent in the same period; 200% for the developed agent who contacts two other agents in the same period; and 50% for the buying agent who takes two periods to contact another agent similar to that defined in Ayyadi and Maaroufi (2018), and Kumar et al. (2022).

The scenarios required changes for the ABM. In inertial, the acquisition and maintenance costs per model increased annually by 1.3% depending on the average inflation rate in a pandemic-free scenario (IBGE, 2022). The battery capacity and autonomy increased by 20% every two years (IEA, 2023). The charging time was progressively reduced from 2035 to 40 min (National Geographic, 2022). The global convergence required insertions of parameters in the acquisition costs reduced by 25%, starting in 2025, considering the industrialised product tax exemption as indicated in Brazilian law number 13,755 (Route 30). In the biofuel protagonism scenario, according to Anfavea (2023), the demand for hybrid types of EV – hybrid electric vehicle (HEV), plug-in hybrid electric vehicle (PHEV) with flex technology that allows fuelling both with gasoline and ethanol, and assisted by electric motors – tends to increase. Brazilian government initiatives have expanded the production and use of sugar cane ethanol as an automotive fuel over the last 20 years to offset the negative effects of oil price increases (Hallack et al., 2020). In this scenario, the acquisition costs per model were adjusted with an annual increase of 1.3% based on the average inflation rate, according to the (IBGE, 2022), and the maintenance costs were readjusted due to maintenance plans for combustion engines, meaning an increase of 15.5% per year (Sindipeças, 2022).

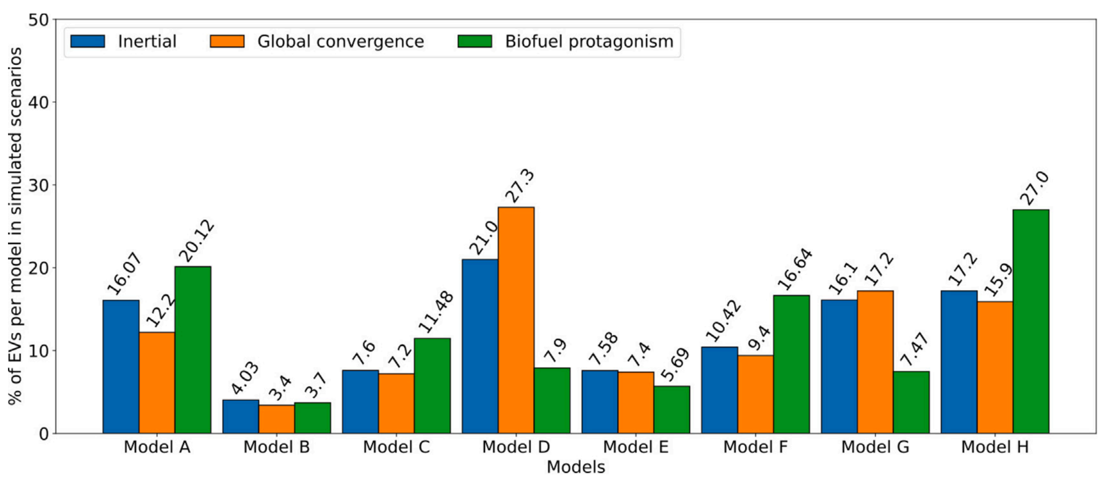
Fig. 5(a) presents the market penetration for EV for each scenario. Fig. 5(b) highlights adoption by vehicle type in the inertial scenario, global convergence, and biofuel protagonism. Results in Fig. 5(b) indicate that there has been no change in the order of the most adopted vehicles in the inertial and global convergence scenarios. Model D is the most adopted, followed by models H and G, which have the lowest acquisition costs. In the biofuels, the protagonism scenario shows model H as the most adopted, followed by models A and F. These models are hybrid EV with the most significant changes regarding the decision factors (range, maintenance cost, battery capacity). The H model showed the most significant increase in autonomy (653.70 km), despite not having the lowest purchase price.

6. Discussions

The aim of this study was to propose an agent-based model and simulation (ABMS) to analyse the market penetration of EV in Brazilian market based on factors that influence adoption to predict vehicle market share for 2035. The forecast was based on agent preferences regarding the acquisition cost, maintenance and recharging costs, battery capacity, range, and charging time for the types of vehicles studied. These results provide insights that help policymakers and transportation planners identify future EV market share in Brazil.



(a) Penetration of EV by scenario (2021 - 2035).



(b) Penetration of EV by model (2021 - 2035)

Fig. 5. Penetration of EV by scenario (2021–2035). *Scenarios:* Inertial — adoption rates follow the current pace with no targets set; Global convergence — acceleration in adoption rates follows the movements already underway in more developed countries; Biofuel protagonism — privileges for biofuels with similar "Inertial" scenario strategies.

The factors were classified into two groups as proposed by Singh et al. (2020), where acquisition, maintenance, and recharging costs are defined as financial situational factors, and charging time, range, and battery capacity are limited as technological situational factors.

As a result, financial situational factors have the highest impact on EV adoption. It is noted that vehicles with lower acquisition and maintenance costs (D, H and G vehicles) present adoption rates above 15% in the inertial scenarios and for global convergence. Even vehicle H presents a significant adoption rate (27%) in the biofuel scenario, highlighting the impact of the lower cost in the adoption process. Another point can be observed about vehicle A, which showed significant adoption rates in the inertial and biofuel scenario, although this vehicle presented a high maintenance cost. The reason behind this result lies in the fact that despite the high maintenance cost, the acquisition cost of this vehicle is considerably lower compared to other models on the market. This finding indicates that the initial acquisition cost plays a significant role in adopting an EV, even if it means dealing with higher maintenance expenses over time. In this sense, it is essential to emphasise that reducing acquisition and maintenance costs may be necessary to boost further EV acceptance and penetration in the Brazilian market. To achieve more affordable prices, a joint effort between governments, car manufacturers and automotive stakeholders is needed to develop strategies that reduce production costs and increase the scale of EV production, resulting in a reduction in acquisition costs (Bitencourt et al., 2023).

Regarding technological factors, in the biofuel protagonist scenario, the adoption rates may indicate that the combination of lower costs with battery capacity and range, mainly related to the outcome of vehicle A (above 20%), become factors that increase the adoption rates of the agents created in the model. This perspective highlights the importance of considering not only a single element but also the combination of different aspects when analysing EV adoption. This result introduces two possibilities for increasing the adoption of EV rates in the Brazilian market. First, the need for investments in EV charging infrastructure in Brazil includes expanding the charging infrastructure network across the country, ensuring convenient access to charging stations and integrating renewable energy sources to power these stations. Public and private sector collaborations can be initiated to accelerate infrastructure development and remove infrastructure-related barriers to EV adoption (Bitencourt et al., 2021). At the same time, it is essential to invest in research that combines hybrid supply systems, such as the use of biofuels together with electricity, to explore innovative solutions that can meet the needs and preferences of consumers (da Silva César et al., 2019).

The results of our research are complementary to previous works developed on EV diffusion models in the Brazilian market, as they include aggregated data on EV market penetration generated from disaggregated data on the market share of specific vehicles over time. This set of results showed that, even under different conditions, EV adoption rates will grow until 2035 due to the behaviours of the ABMS and Bass model concerning the defined parameters. Furthermore, we realised that, in addition to acquisition cost, different factors can influence adoption rates, extending the proposition of previous work, as in Benvenutti et al. (2017) and Grangeia et al. (2023).

As to the managerial implications, our results show that in all simulated scenarios, there will be an increase in the number of EV adopters by 2035. However, the rates are still low when compared to the values of vehicles with an internal combustion engine, indicating the need to use more successful strategic mechanisms to increase EV market share, in line with the decarbonisation programmes of the Brazilian transport sector, one of the main gas emitting sectors in Brazil. From an academic perspective, by considering the consumer as an agent influenced by the interaction between aggregate level factors and technical factors, including autonomy, battery capacity, maintenance, recharging time, and acquisition cost, our work addresses an issue that has not been studied before. In this context, it is relevant to evaluate scenarios based on technical and economic parameters that help develop actions to improve Brazil's EV adoption rates.

7. Conclusions

Coupled with the growing worldwide concern with reducing pollutant gases from light-duty vehicles, we directed our research to understanding EV adoption processes because of all the efforts and the collective movement to facilitate electrification of the world's transportation fleet. From the results obtained in this study, it is possible to highlight two contributions. First, the paper contributes by combining models to represent a complex process so that the proposed ABM simulates the behaviour of the consumer agent given a decision structure. These agents were aggregated to generate cumulative adoption numbers through the Bass model. This combination enables calibration systems for different types of parameters, which extends previous studies on actions to improve EV adoption rates in Brazil. Second, by investigating market introduction of the innovation using a multi-year dataset of EV buyers and marketed vehicle models, the results of this study contribute to the literature on EV adoption in the Brazilian market. We conclude that acquisition cost remains the main driver of the process. However, barriers to electric mobility are related to several vehicle-specific factors such as range, maintenance costs, battery prices, and acceptance. Analysing such factors is essential in extending the understanding of EV adoption in Brazil.

As a limitation, the proposed ABM considers only consumer agents in adopting EV. This can be explored in future research evaluating new agents, such as manufacturers, the government, and the supply chain. Another limitation relates to the diversity of factors computed in the model in the current version. Numerous other factors can be described, including those related to psychological factors. This limitation can also guide future research since studies have clarified consumer reasons for buying a car with a particular propulsion system, including functional, symbolic and hedonic aspects as proposed in Kangur et al. (2017). Furthermore, the challenge of integrating different types of modelling levels into model outputs is complex and can be explored in future research, mainly related to parameterising the Bass model data for the Brazilian market. Another challenge that needs to be explored is creating a hybrid model capable of associating the Bass model developed from the SD perspective and ABM creating a model capable of reacting to different data patterns and exploring different scenarios at aggregate and disaggregate levels. In the experimental part, it is recommended to work on the ability to distribute agents in a given region to check the differences between the adoption curves of regional EV, as developed in Noori and Tatari (2016) and Lee et al. (2019).

In the quest for sustainable development, we can highlight several promising areas of future research. First, investigating how innovative technologies that minimise environmental impacts and resource use can influence consumer choices and behaviours towards more sustainable practices, such as the circular economy and responsible consumption principles, could provide valuable insights. Moreover, conducting environmental and sustainability assessments to evaluate the environmental performance of EV and the impact of supply infrastructure services could lead to the development of more environmentally friendly and socially responsible products and services. Finally, exploring international oil price fluctuations and the growing concern with Brazil's energy matrix are topics of great relevance for the EV market, leaving a research gap to be explored.

CRediT authorship contribution statement

Rodrigo Furlan de Assis: Conceptualization, Methodology, Data curation, Modelling, Formal analysis, Visualization, Writing – original draft, Writing – review & editing. **Fabio Müller Guerrini:** Conceptualization, Methodology, Supervision, Validation, Writing – review & editing. **Luis Antonio Santa-Eulalia:** Validation, Writing – review & editing. **William de Paula Ferreira:** Methodology, Formal analysis, Visualization, Funding acquisition, Supervision, Writing – review & editing.

Declaration of competing interest

The authors declare no conflict of interest.

Data availability

Data will be made available on request.

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