Forecasting the diffusion of electric vehicles: An agent-based model including household choice and social effects of coherence and communication

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SHORT SUMMARY

To address the problem of forecasting the diffusion of innovations, we propose an agent-based model to forecast the electric vehicle (EV) market, that considers fuel type choices, simultaneously tackling household decision-making and cognition (in the form of coherence evaluation), as well as processes of communication between households in their social network, which are the drivers of diffusion in the social network. We use a latent class discrete choice model to characterise fuel type choice at the household level, including preference heterogeneity, along with attitudinal and emotional effects with the hot coherence (HOTCO) model of cognitive consistency. Our agent-based model also incorporates direct and indirect communication between households in the network. Results highlight the need for diverse measures targeting vehicle purchase, ownership, and usage dimensions to accelerate EV market adoption.

Keywords: Agent-based model, Diffusion of innovations, Electric vehicles, Hot coherence, Social influence

1. INTRODUCTION

Electric vehicles (EVs) play an important part in the decarbonisation of the transport sector. Despite the vast support from governments worldwide –but especially across developed countries (International Energy Agency, 2024) –, EV diffusion has been difficult. A vast literature has tried to understand what affects the adoption EVs and to simulate their market diffusion. However, predicting the demand for EVs is challenging, mostly due to the complex relationships between individual preferences and social influence that determine the propensity to adopt an alternative that has yet to reach its market potential and therefore can still be considered "innovative". The deployment of EVs can be interpreted as the aggregate result (*diffusion*) of a series of decisions taken at the household level (*choice*), which in turn are influenced by the overall levels of adoption in the social network (Domarchi and Cherchi, 2023b).

Agent-based models (ABM) are currently the most popular framework to model all these aspects of diffusion of innovations (Zhang and Vorobeychik, 2019; Mehdizadeh *et al.*, 2022). They are in fact simplified representations of the social network whose main components (the agents) are capable of flexible and autonomous action according to pre-established behavioural rules which determine their own decision making and the interaction with other agents in the network. Diffusion emerges as a product of these interactions (Nikolic and Kasmire, 2013). While ABM are flexible enough to assess the effect of several variables and contextual conditions in the diffusion process, their reliability and forecasting ability can often be undermined by the lack of an appropriate theoretical framework for their behavioural rules, or the absence of calibration, validation, and grounding (Domarchi and Cherchi, 2023b).

In fact, only a handful of ABM studies addressing EV diffusion in the literature use appropriate models (in the form of DCM) to simulate the choice side of the decision process as part of their agent decision rules. In addition, in their most basic formulation, DCM are "static" – their parameters do not change over time –, which means that, when used, they need to be adapted to address the dynamic nature of the diffusion process (i.e., the positive impact of adoption in the social network on the probability of buying an EV). Similarly, although studies focusing on the choice side of the problem have assessed the role of psychological traits such as pro-environmental attitudes, innovative character, car performance anxiety, and the symbolic value of the car, in EV choice probabilities (Liao *et al.*, 2017; Wicki *et al.*, 2023), these dimensions have seldom been added to diffusion-substitution models. Cognitive consistency theories, which offer a more nuanced understanding of the relationship between attitudes, emotions, and behavioural intentions, have been proposed as a flexible method to incorporate these aspects in ABM simulations. However, their use has been limited (Wolf *et al.*, 2015; Kangur *et al.*, 2017; Liang *et al.*, 2022), and never in integration with a DCM.

Preference heterogeneity has also been found to play a significant role in the probability of adoption (Guerra and Daziano, 2020; Li *et al.*, 2020; Rommel and Sagebiel, 2021; Domarchi *et al.*, 2024a); however, as most ABM with DCM components tend to only include simple specifications (such as MNL), they fail to account for this effect. Finally, while every diffusion model includes a social diffusion component that roughly complies with Rogers (2003) innovation diffusion theory, this is usually implemented in a simplified fashion, without a deep analysis of agent interaction and communication.

In this paper, we propose an ABM that addresses EV diffusion and substitution[1].Our model considers fuel type choices, simultaneously tackling household decision-making and cognition (in the form of coherence evaluation), as well as processes of communication between households in their social network, which are the drivers of diffusion in the social network. Our ABM is initialised with data grounded in the study area (UK context), and using parameters calibrated to ensure that they represent the market of interest. As our interest lies on the behavioural and social side of the EV diffusion problem, the proposed framework is a single-agent ABM which only addresses other stakeholders (car manufacturers, car sellers, energy providers, government) indirectly, as part of their modelling scenarios. Our paper contributes to the specialised literature by:

1) Addressing preference heterogeneity in choices for vehicle segments and fuel types – an effect largely neglected in the literature – using a latent class discrete choice model (LCCM) as the behavioural rule for agents in the model.
2) Incorporating attitudinal and emotional effects into the decision-making process with the hot coherence (HOTCO) algorithm, which considers the interaction and compatibility between individual beliefs and attitudes and their perceived effects on decision outcomes. The method, which allows for non-additive and non-linear effects of attitudinal evaluation in individual choices, has seldom been used in the context of ABM, but never concurrently with a DCM.
3) Analysing the effects of communication with other agents in the attitudinal and emotional evaluations of vehicle segment and fuel type alternatives, simulating direct and indirect communication between agents in the social network. These two effects have also never been used in conjunction with a DCM behavioural rule in an ABM simulation environment.

The model was applied to the North-East region of England, using data from the National Travel Survey (NTS; Department for Transport, 2021) which, at the moment of collecting the information, were available for the 2002–2020 period.

[1] We included hybrid electric vehicles (HEVs) in our analysis because they currently represent, for many users, a reasonable compromise between the more traditional ICE vehicle technology and the more challenging EVs. The differences between these two fuel types are highlighted when appropriate.

2. METHODOLOGY

The model we propose is based on the following assumptions/modelling steps:

- H1: *Global behaviour emerges as a result of individual decision making and agent interaction*. Since car ownership is typically a family decision, the decision unit (*agent*) is represented as a household that possesses a series of socioeconomic attributes, a specific geographic location, and a certain number of vehicles (which can be zero) with their own attributes. In addition, households store personal information about one of their inhabitants, defined as the lead of the household, including their age, gender, and educational level. It is also assumed that the lead of the household possesses attitudinal and affective evaluations of both the available fuel types and the transport needs of the households.

- *H2: Households (agents) interact within a social network*. We build a social network to simulate the agents' interactions in the simulation environment. The likelihood of two agents being linked depends on their socioeconomic attributes, the characteristics of their vehicles, and their geographic locations.

  H3: Households decide whether they need to buy an additional car or discard one of their current cars. We model these decisions using a DCM where the probability of changing the current level of car ownership is modelled as a function of socioeconomic individual and household attributes, along with significant life events such as residential relocations, employment switches, and changes in household size. We estimated the model using a longitudinal sample of 10,067 UK households sourced from eight waves of the Understanding Society Survey (University of Essex *et al.*, 2020), with full results reported in Domarchi and Cherchi (2023a). According to this model structure, we implemented this decision in two successive steps. First, the household decides whether it needs to discard one of its cars or buy an additional one, with cars removed or added to the simulation accordingly. If no changes in car ownership levels are required, then vehicle holdings stay unchanged.

  H4: Households update their attitudinal and emotional appraisals by direct communication with other households.

  - We use the hot coherence (HOTCO) model (Thagard, 1989;2006) to address cognitive consistency in each household. Households in the ABM are mapped to respondents from a dedicated survey aimed to collect the information required to estimate the parameters of the HOTCO model. In the HOTCO model, the decision-making process is represented as a coherence network linking transport motives with decision outcomes. An iterative algorithm is run to obtain activations and valences that represent the attitudinal and emotional responses to each alternative. The data collection and modelling processes are reported in Domarchi *et al.* (2024b).

  In turn, the HOTCO model allows addressing direct communication between agents as a process of information exchange which results in updated HOTCO inputs that change at each time step *t*. The updated score ${s_d}^{(t)}$ for HOTCO input d at time step t is calculated as:

$$
{s_d}^{(t)} = \begin{cases} -1 & \text{if } {s_d}^{(t-1)} < -(1+\Delta s_d) \\ +1 & \text{if } {s_d}^{(t-1)} > (1-\Delta s_d) \\ {s_d}^{(t-1)} + \Delta s_d & \text{in other case} \end{cases} \qquad (1)
$$

  Where the Δs_d values are the mean score changes per HOTCO input d. The ${s_d}^{(t)}$ are bounded to the $[-1; +1]$ range, as the rest of the HOTCO inputs. This updating process ensures that the beliefs and emotional appraisals of each need and action are adjusted for both agents as a product of their information exchange. Once all inputs are set to their new values, each agent updates the resulting activations and valences for all the nodes in the connectionist network, using the HOTCO algorithm. The Δs_d parameters were sourced from the results of a "before-and-after" experiment where respondents to the dedicated survey were submitted to narrative messages about EVs. Full results of this experiment are available in Domarchi (2023)

- *H5: Households decide whether they require to replace one of the vehicles they currently own.* Mathematically, this is a probabilistic model to determine if a vehicle will be replaced, as a function of its age and the current length of ownership.

- *H6: Households observe the current adoption rates in their network to evaluate their willingness to consider the innovative alternatives.* An indirect communication process is carried out, whereby households evaluate their knowledge of the recent decisions of other households in their social network and use this information in their own choice. We model this stage using an adapted version of the willingness-to-consider (WtC) parameter (Struben and Sterman, 2008). Assuming that choice is modelled using a LCCM structure, WtC is a household- (q) and alternative (i)-specific parameter assumed to deflect the class-specific choice probabilities, reflecting alternative familiarity. For familiar and well-established technologies, $WtC_{iqt} = 1$. Conversely, if the household is completely unfamiliar with the technology, $WtC_{iqt} = 0$. The intermediate case arises when the household has still not adopted the technology but at least one neighbour in the social network has. In this case, we model WtC_{iqt} as a monotonously increasing function of the current (local) market share MS_{iqt} during time t, as suggested in Struben and Sterman (2008). We operationalise WtC_{iqt} as a random variable following a truncated Normal distribution with mean:

$$\overline{WtC_{iqt}} = \frac{1}{1 + \exp\left(-\varepsilon \cdot \left(MS_{iqt} - w^*\right)\right)} \tag{2}$$

  Where ε and $w^*$are calibration parameters. In particular, w^* represents the expected mean value of WtC when adoption in the local network reaches 50%, and ε is the slope of the WtC at that point. The resulting distribution requires to be bounded to the [0,1] interval consistent with the definition of WtC, and the standard deviation is defined as $\overline{WtC_{iqt}}\big/4$. Further details are provided in Domarchi (2023).

- *H7: Finally, households choose a specific vehicle (determined by a car segment and a vehicle type),* as a function of vehicle attributes – e.g., purchase prices, operation costs, mechanic characteristics, and geometric dimensions –, socioeconomic and geographic attributes, external elements such as the fuelling/charging network or the effect of policy measures, and the outcome of the communication process. Mathematically, this decision is modelled using a LCCM that includes cognitive consistency (HOTCO) effects. The class-specific choice probabilities also include the WtC_{iqt} parameter from equation (2), using the following expression:

$$P_{iqt|s} = \frac{WtC_{iqt} \cdot \exp\left(\sum_k \theta_{iqks} X_{iqkt}\right)}{\sum_{A_j \in A(q)} WtC_{jqt} \cdot \exp\left(\sum_k \theta_{iqks} X_{iqkt}\right)} \tag{3}$$

  Where X_{iqkt} are values for attribute *k*, household *q*, alternative *i* in time step *t*, and θ_{iqks} are parameters estimated for household *q* belonging to class *s* and associated with attribute *k* and alternative *s*. The θ_{iqks} parameters were estimated using data from the dedicated survey in H4. Full results are reported in Domarchi *et al.* (2024a).

- *H8: Households engage in this decision-making process over time.* The process is simulated dynamically, with each iteration representing a time step. The main (socioeconomic) agent attributes and the configuration of the social network remain unaltered during the course of the simulation, while the vehicle attributes change over time. The decision-making process occurs iteratively over the simulation period, with households permanently reassessing their car holdings, engaging in (direct and indirect) communication, deciding if their vehicles require replacement and defining their preferred alternative if this is the case.

Figure 1 shows the scheme of the overall decision-making process as described so far. In this figure, diamond boxes represent behavioural steps framed as *Yes/No* type questions that the household must answer before continuing with the process. Rectangles, on the other hand, represent decisions that result in changes in household or vehicle attributes. The inputs and outputs of these modelling steps are inter-related, and their combined result is a profile of vehicle purchases per fuel type for each simulation step (year).

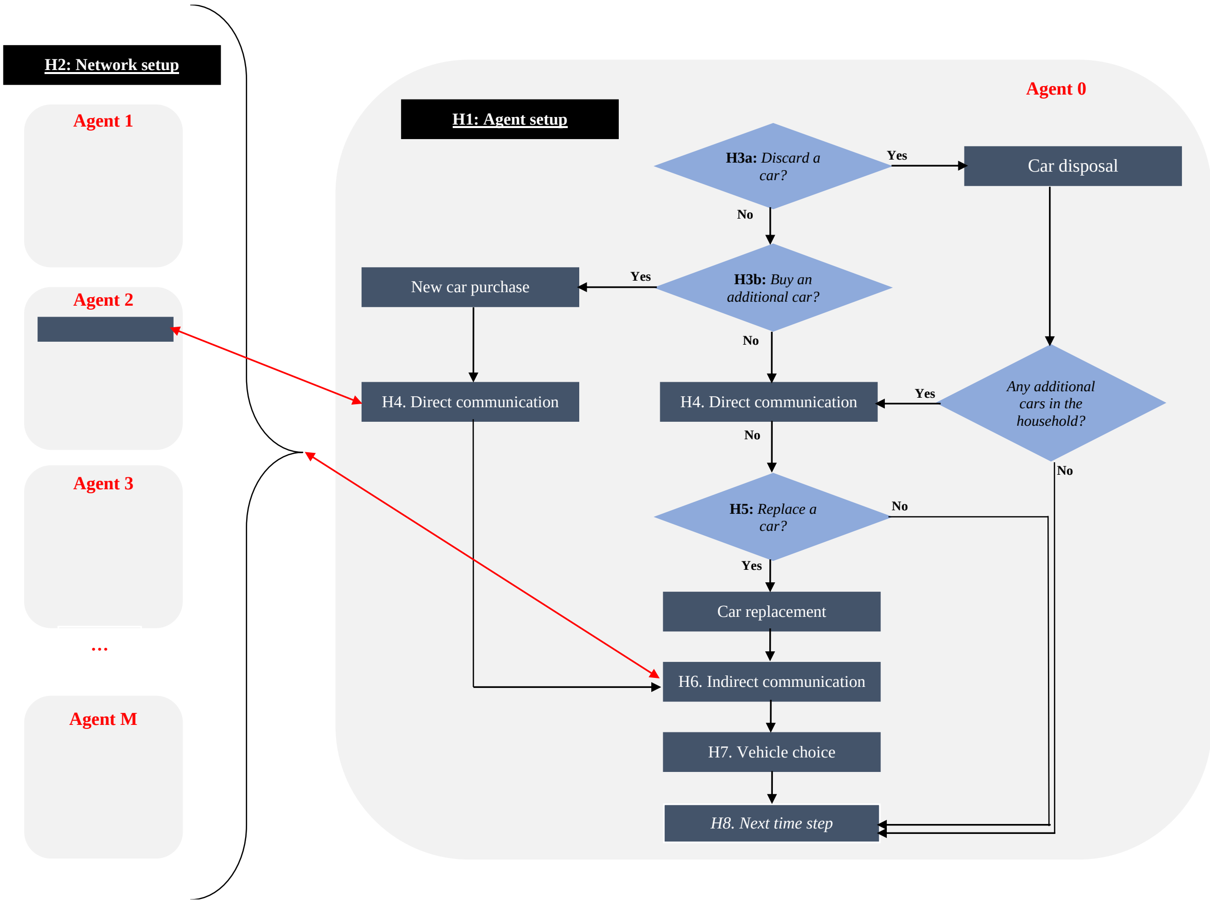

Figure 1. General overview of the model

3. RESULTS AND DISCUSSION

We calibrated our model using a *base case scenario*, built considering average market parameters for the 2021–2022 period (known at the time of calibration). During the calibration stage, we aimed to determine suitable values for the ε and w^* parameters in equation (2), and the structure of the social network. We ran our model for several combinations of these parameters. We chose the parameters that minimised the square mean prediction error, evaluated as the difference between modelled and actual market shares per fuel type. We chose a grid of parameters whose combinations yielded mean square prediction errors of around 1–2%.

For forecasting the 2021–2049 period, we defined a base case scenario and 10 policy scenarios. The base case scenario assumes an evolution of market parameters that is similar to the one observed in the previous years. We relaxed this assumption in the policy scenarios.

The first two scenarios (1 and 2) assume that the ICE/HEV phase-out will not occur as originally planned. Scenario 1 assumes it will be postponed by five years, and Scenario 2 assumes it will be scrapped altogether (i.e., sales of new ICE/HEV cars will still be allowed). Scenarios 3 and 4 were simulated to obtain lower bounds of the EV diffusion curve over time, as they assume unfavourable market conditions. Scenarios 5 to 9 are used to explore the more optimistic outlook in the EV diffusion curves. They assume policy measures including purchase subsidies (5), improvements in the EV charging network (6), petrol taxes and energy rebates (7), a combination of all these measures (8) Scenario (9) tests the combined effects of these optimistic assumptions and the negative outcome of the "no-phase out" scenario (2). Finally, Scenario 10 assumes that an aggressive advertisement campaign is conducted by the government during the first years of EV adoption (2021–2030), promoting the benefits and positive effects of owning and using an EV, with households responding according to our HOTCO experiment.

Figure 2 and Figure 3 illustrate the evolution of the EV market in terms of sales and total number of cars during the simulation period in each scenario.

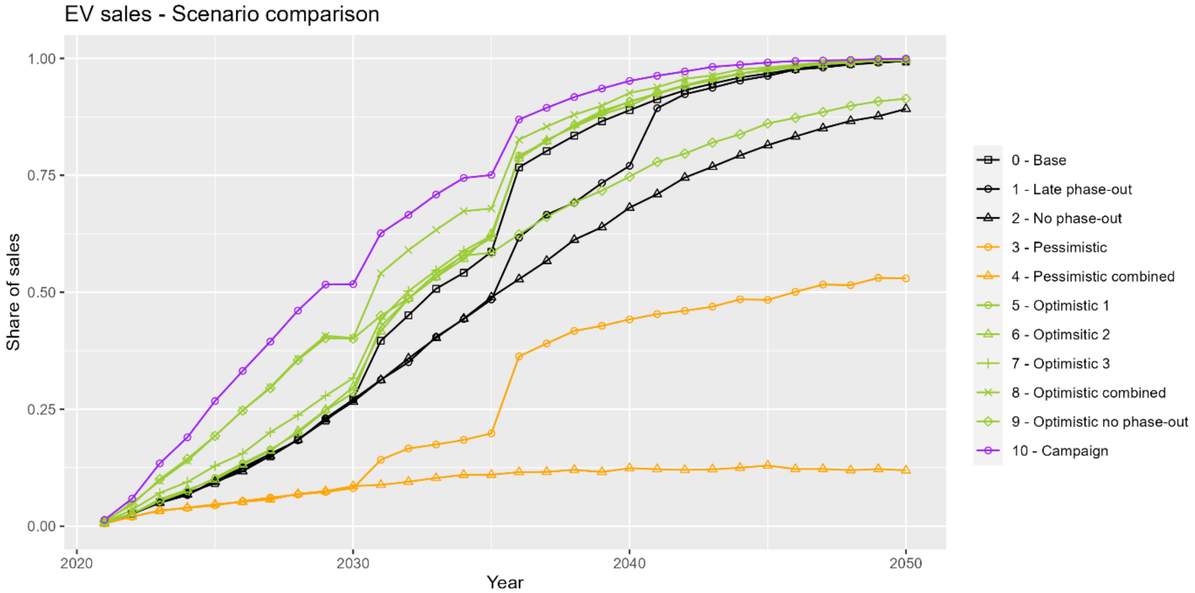

Figure 2. ABM results – Evolution of EV sales by scenario

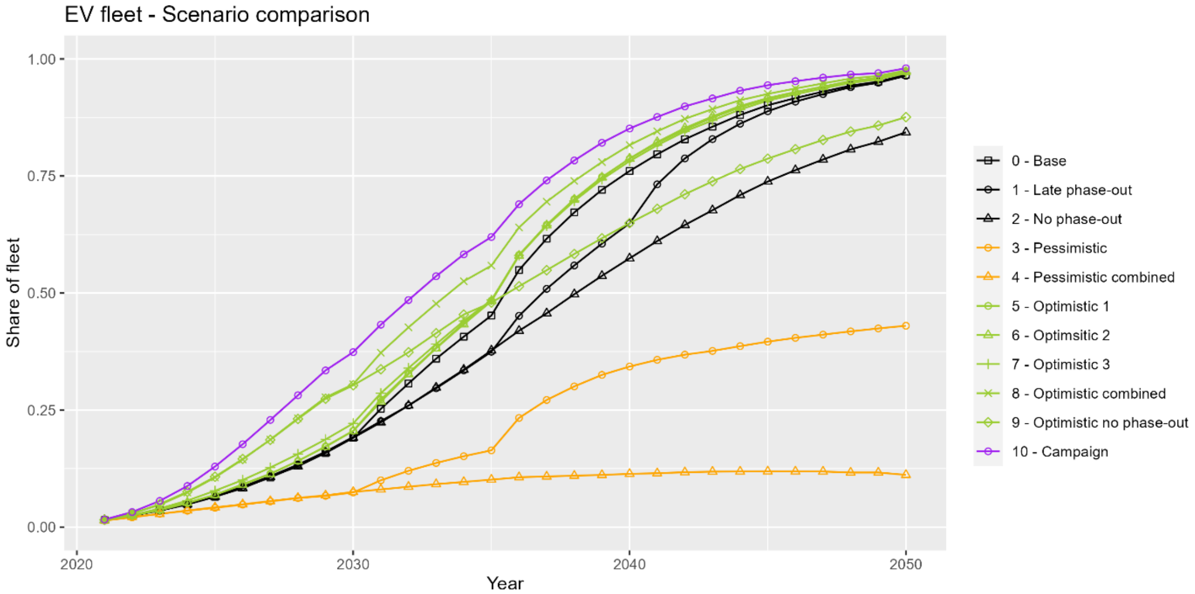

Figure 3. ABM results – Evolution of EV fleet by scenario

Both pessimistic scenarios generate significantly lower shares for EVs over time, with the most extreme case (*Scenario 4:* Pessimistic – Combined) reaching a final share of 11.1%. The base case scenario performs similarly to the optimistic (green) scenarios in the final years of the simulation; however, the positive effects of increased adoption induced by policy measures imply that a significant level of decarbonisation in the car fleet can be reached earlier. The highest adoption rate is reached in *Scenario 10 ("Campaign")*, which assumes a highly effective investment in advertisement, and a widespread positive reception to it. While not an entirely realistic outcome, it still shows that attitudinal shift might be a significant driver of EV uptake.

It should be noted that not even the most optimistic scenarios evaluated with the model generate a situation where the fleet of EVs reaches 46% of the total number of cars in the study area by 2030. This is a concerning result, even if the share of EVs is higher than 97% in all the optimistic scenarios by 2050, as the climate emergency is pressing, and a faster uptake is required earlier to reach the desired levels of fleet decarbonisation. More aggressive policy measures might be required to ensure that this objective is met.

4. CONCLUSIONS

We built an ABM to forecast EV adoption from a behavioural-based perspective, simultaneously addressing household decision-making and cognitive consistency, along with processes of communication between households in a social network. We evaluated several policy scenarios, simulating both favourable and unfavourable scenarios for EV diffusion in the England market. Our results confirm the need for combined policies to ensure that the personal car fleet decarbonisation follows the required patterns for the expected reduction in carbon emissions. The most effective approach to improve EV adoption is to combine measures directed at different dimensions of the problem. Purchase subsidies might be successful in certain contexts, but less contentious measures such as energy rebates, or relevant improvements to the EV charging network, can reach comparable results with lower risks of political or ethical concerns, and eventually lower amounts of investment. One of the most important measures in this direction is the ending of the sales of new petrol and diesel cars and new HEVs, currently planned for 2030 and 2035, respectively.

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