University of Southampton

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

Seminar for the Transportation Research Group
University of Southampton

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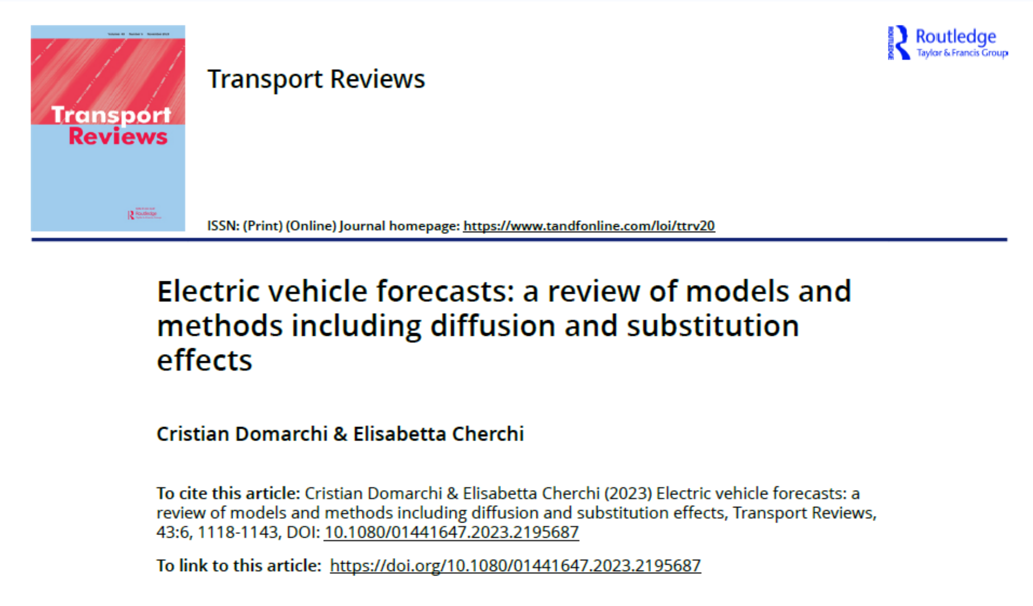
INTRODUCTION

- The transport sector is witnessing major technological innovations.
- Innovative alternatives will imply significant behavioural changes.
- Predicting demand for transport innovations is required for:
  - Understanding and predicting trends.
  - Planning and formulating policy measures.
- **Key question: How will users respond to transport innovations?**

INTRODUCTION

- Governments have been encouraging the uptake of low emission vehicles, with measures to reduce the cost gap between alternative fuel vehicles (AFVs) and internal combustion engine (ICE) vehicles.
- Sales have been increasing over time; however, market shares remain low, and lower than predicted (Domarchi & Cherchi, 2023).



Transport Reviews

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Electric vehicle forecasts: a review of models and methods including diffusion and substitution effects

Cristian Domarchi & Elisabetta Cherchi

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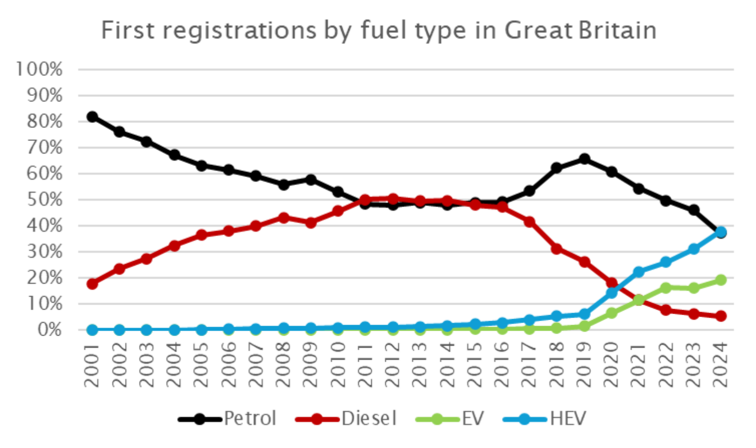
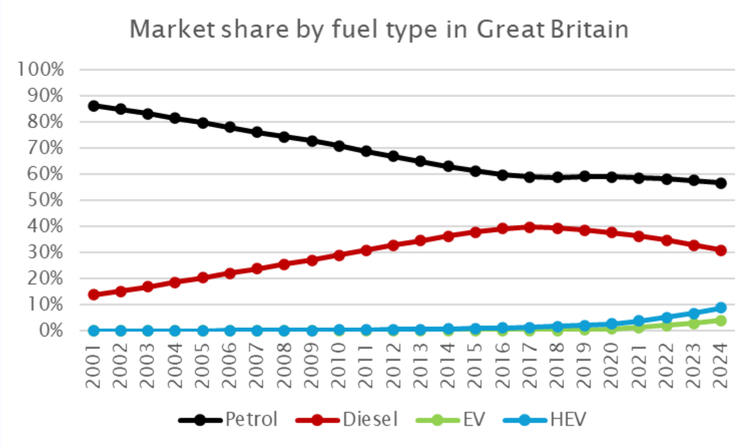




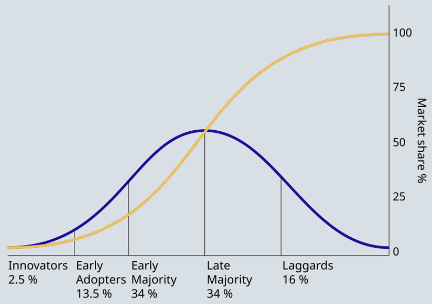
Source: https://www.gov.uk/government/statistical-data-sets/vehicle-licensing-statistics-data-tables
Table VEH1153 – Vehicles registered for the first time

Source: https://www.gov.uk/government/statistical-data-sets/vehicle-licensing-statistics-data-tables
Table VEH1103 – Licenced road using vehicles

INTRODUCTION

- As AFVs are still “innovative” alternatives in the market, forecast models must incorporate **diffusion** and **substitution** components:

- **Diffusion**: Two-way communication between members of the social system.
- Frequently modelled with frameworks that follow the diffusion of innovations theory



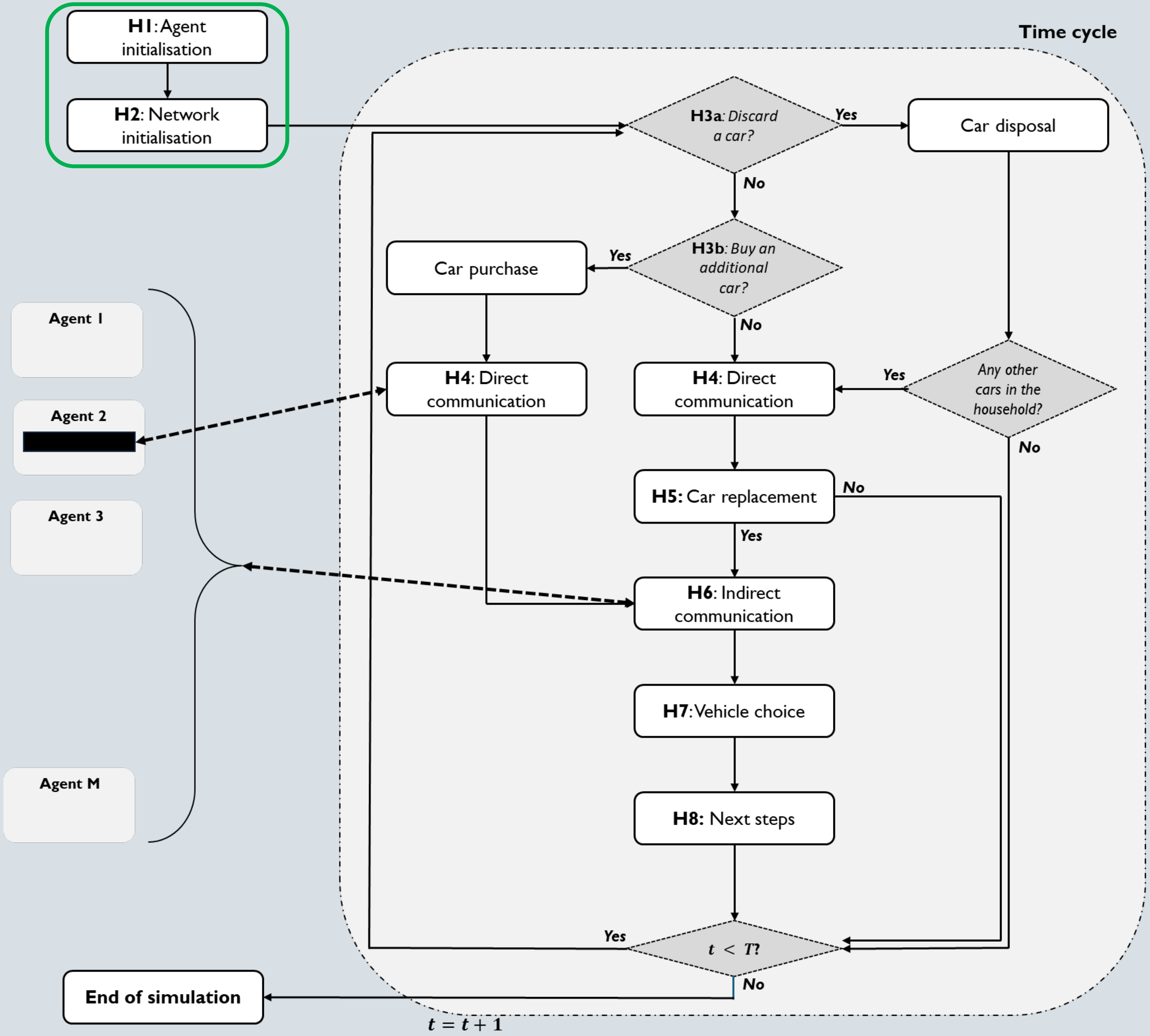
- Generally oversimplified behavioural representations.

- **Substitution**: Choice among fuel types at the individual (or household) level.
- Usually tackled with discrete choice models.
- In early stages, they use stated choice data and cannot properly account for new or less known alternatives in the market.

AIMS AND OBJECTIVES

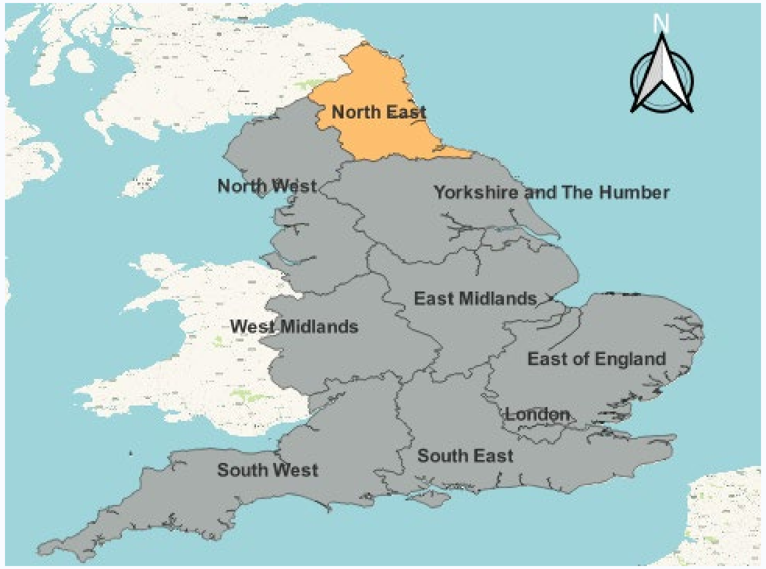
- To propose and validate an integrated diffusion/substitution model for innovative transport alternatives.
- The proposed framework is operationalised as an agent-based model (ABM), programmed in NetLogo.
- The model explicitly considers:
  - advanced substitutional effects
  - social communication
  - diffusion processes
- The AFV market is used as a case study, with a special focus on EVs.

EV-ABM MODEL OVERVIEW

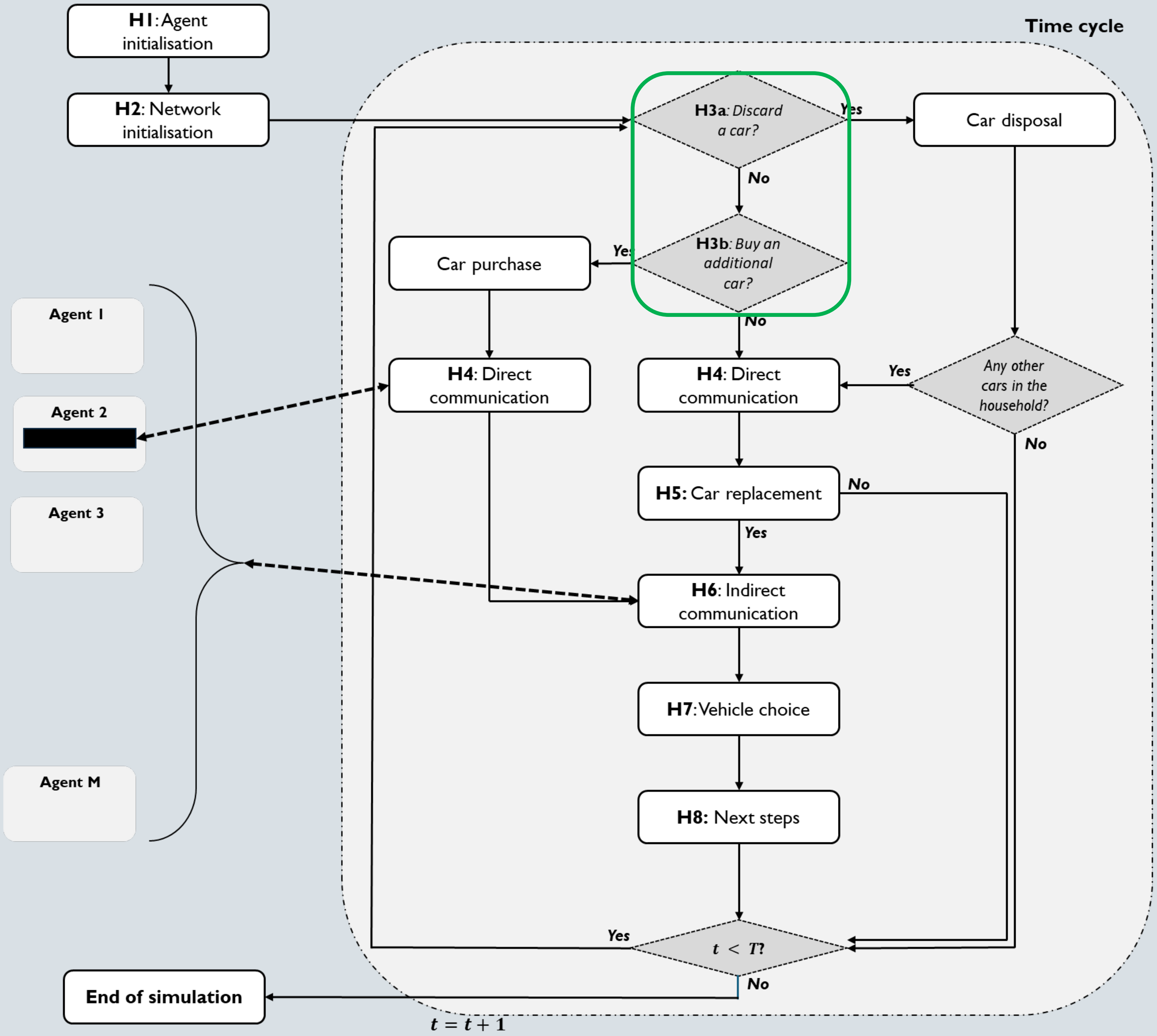


H1 & H2: INITIALISATION

- Our model is a single-agent ABM where agents are **households**, whose information is sourced from the National Travel Survey.
- The households have an approximate location, an initial number of cars (which can be zero), and a set of sociodemographic attributes.
- We establish an **homophily network**, in which agents (households) are linked with “similar” agents in the network.
- The likelihood of two agents being linked depends on their socioeconomic attributes, the characteristics of their vehicles, and their geographic locations.



EV-ABM MODEL OVERVIEW

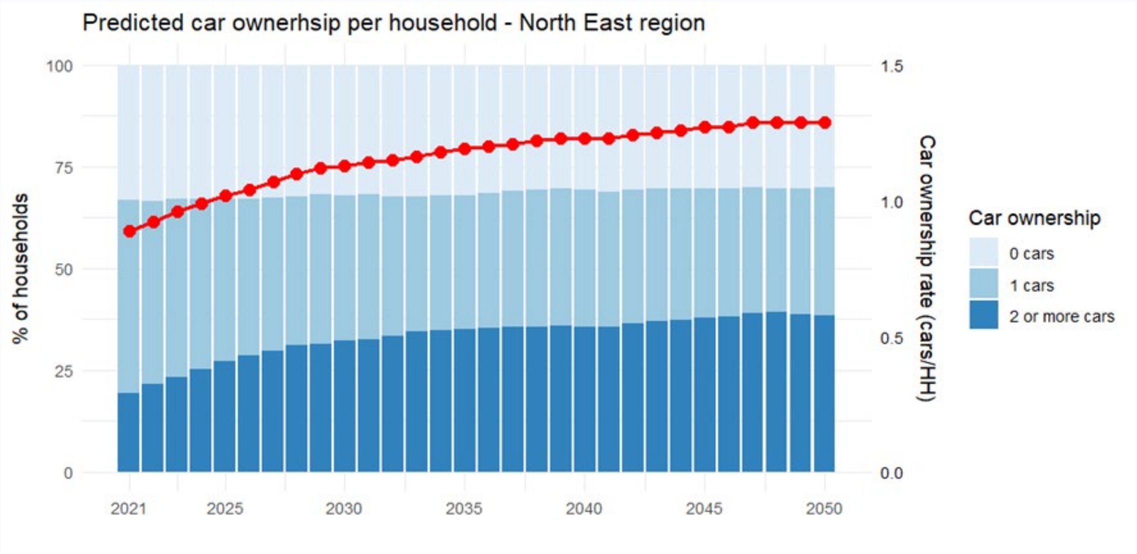


H3: CAR OWNERSHIP LEVEL CHOICE

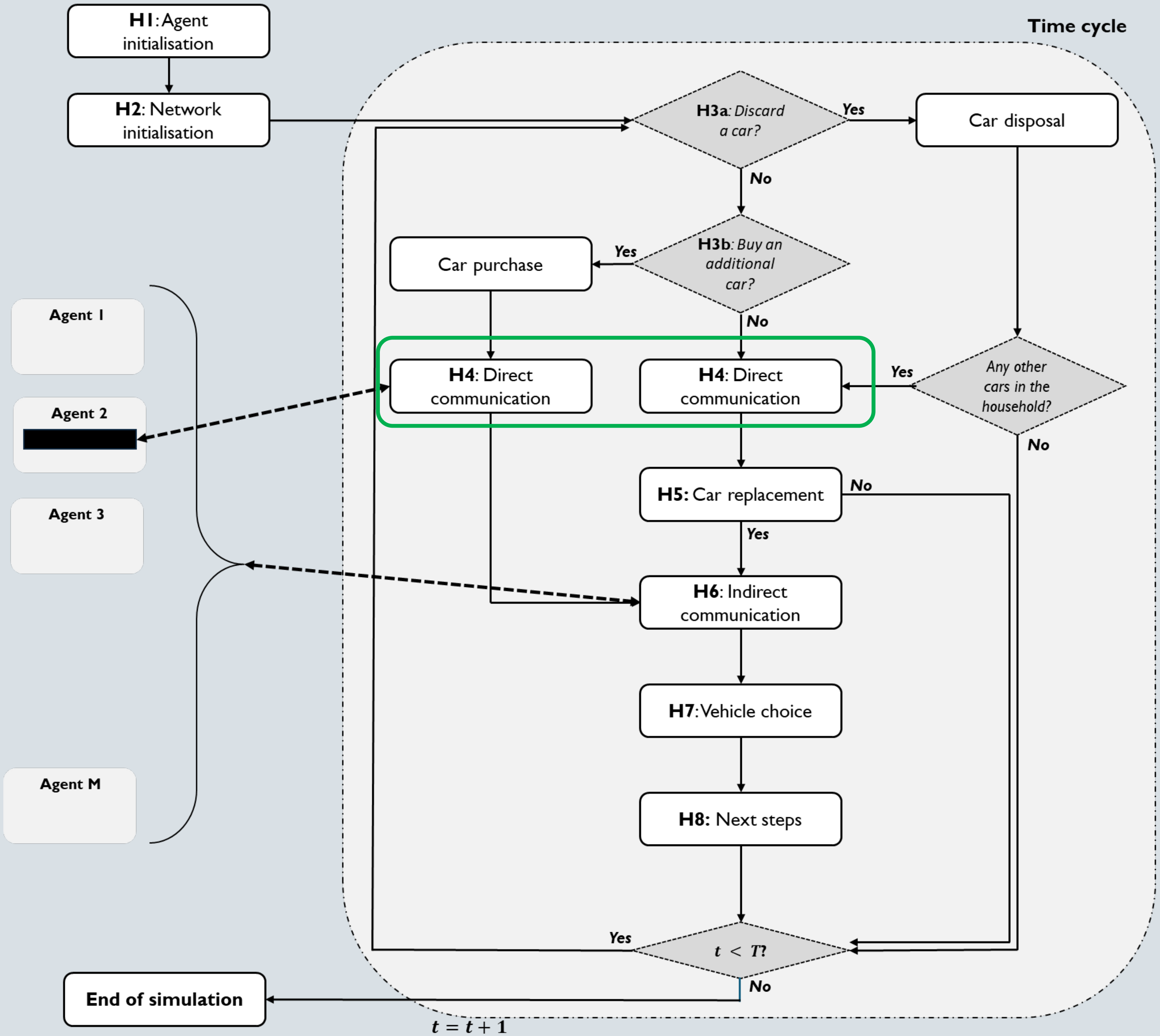
- The ABM includes a **choice model of car ownership level**. Each household q in time step t, can choose among three alternatives:
  - Discard one vehicle
  - Purchase an additional vehicle
  - Keep the number of vehicles in the household constant
- The dependent variables of the model are **life events**, including residential relocations, workplace changes, household merges or splits.
- The model was estimated using a subset of data from the UK longitudinal household survey ("Understanding Society").

H3: CAR OWNERSHIP LEVEL CHOICE

- The model includes **dynamic effects** (choice in time t depends on choice in time $t-1$), which are significant and improve predictive accuracy.
- We predicted car ownership level over the whole forecasting period (30 years) and implemented these results into the ABM simulation.



EV-ABM MODEL OVERVIEW

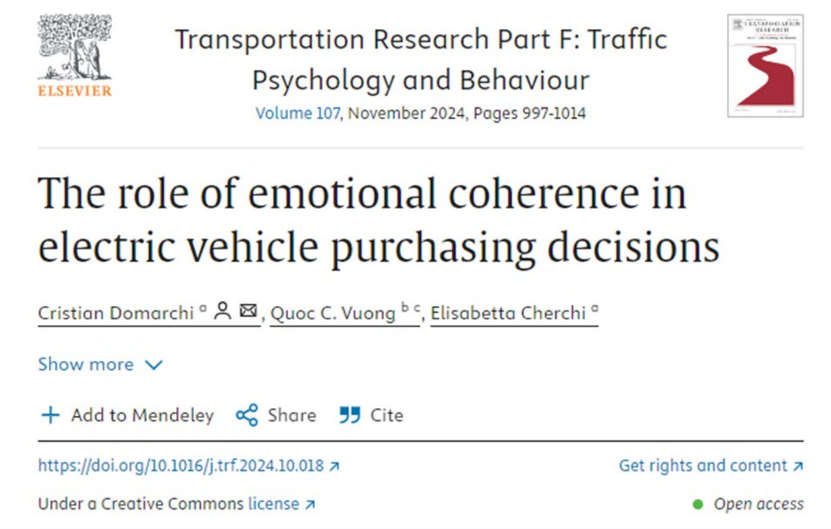


H4: AGENT COGNITION AND DIRECT COMMUNICATION

- We model the effects of psychological variables using the **Hot Coherence (HOTCO) model**, a type of cognitive consistency theory (Thagard 1989, 2006).
- The HOTCO model represents the individual attitudinal formation process as a **connectionist network**:
  - The **needs** to satisfy and the possible **actions** (alternatives) are nodes of this network.
  - The nodes are connected by **links** that represent the degree of perceived **coherence** between needs and actions.
- The decision maker will attempt to maximise the coherence between his/her needs and actions.
- Coherence maximisation is an iterative process, at the end of which each node will have two values:
  - An **activation** value, indicator of attitudinal inclination towards each node.
  - A **valence** value, indicator of emotional appraisal of each node.

H4: AGENT COGNITION AND DIRECT COMMUNICATION

- We conducted a dedicated survey of vehicle owners in England households ($N = 555$) to collect information about HOTCO inputs.
- We modelled fuel type choice as a connectionist network with 10 need nodes (car purchasing motives) and 3 action nodes or alternatives (ICE vehicle, EV, HEV).
- We obtained activations and valences for each of these nodes.


ELSEVIER

Transportation Research Part F: Traffic Psychology and Behaviour

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The role of emotional coherence in electric vehicle purchasing decisions

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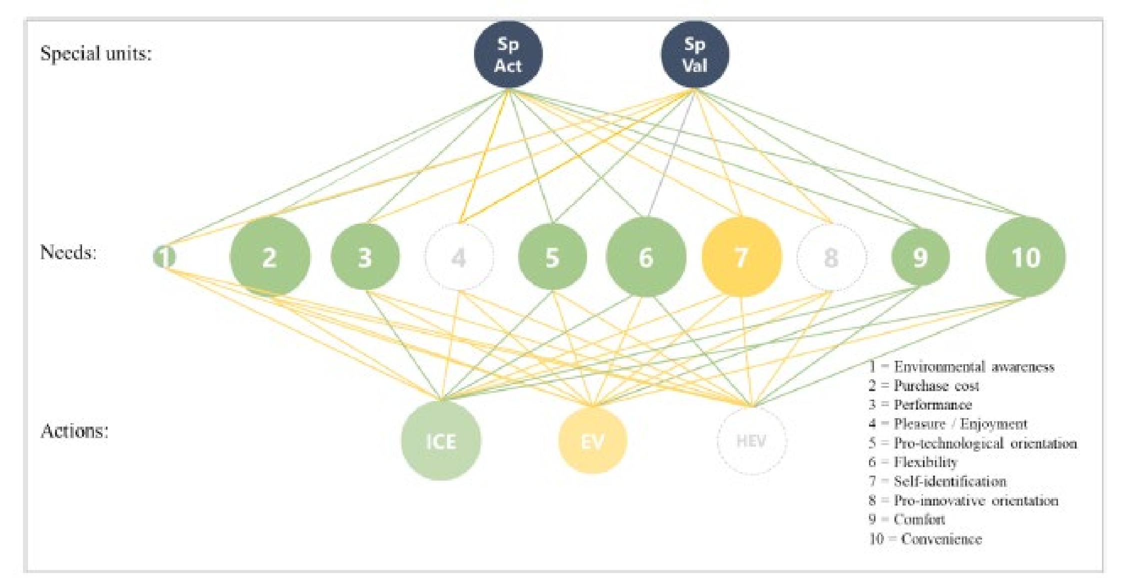
H4: AGENT COGNITION AND DIRECT COMMUNICATION

- This is how a HOTCO network looks after coherence maximisation:



- We implemented the HOTCO process inside the ABM simulation, such that the networks are run for each agent at each time step.

H4: AGENT COGNITION AND DIRECT COMMUNICATION

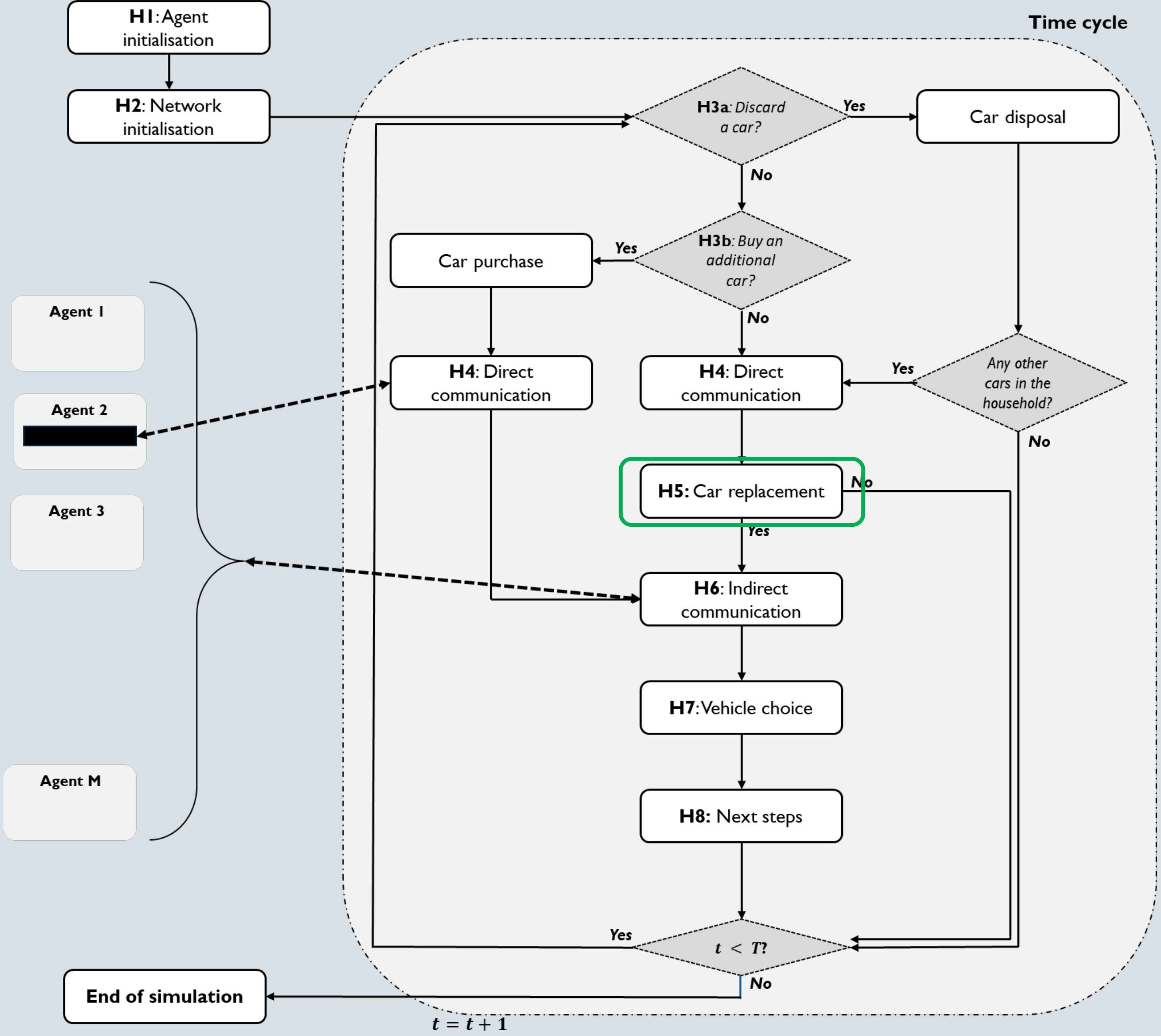
- We conducted a second survey ("follow-up") to study agent communication.
- We aimed at participants from the first survey and obtained 444 valid surveys.
- We built an experiment in which participants were exposed to a **narrative message** about EVs, defined by two conditions:
  - **Polarity**: positive vs. negative.
  - **Appeal**: emotional vs. rational.
- After each message, participants responded to the HOTCO questionnaire again.
- We implemented changes in HOTCO responses into the ABM to simulate agent communication, using the following expression:

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

$s_d^{(t)}$: attitudinal score d at time t
Δs_d: change in these scores, as a result from exposure to a message

- The HOTCO network was updated at each time step as a result of these changes.

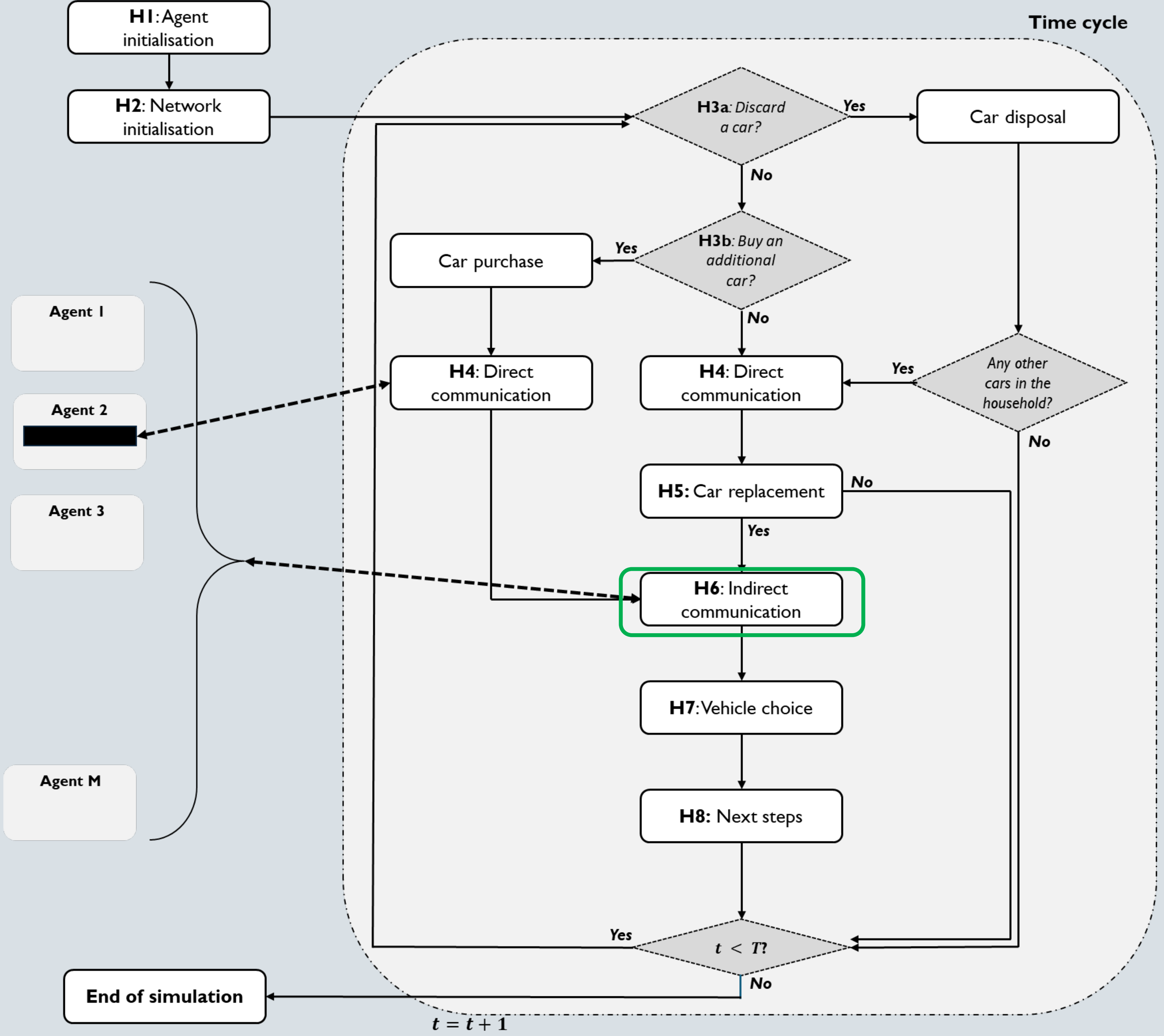
EV-ABM MODEL OVERVIEW



H5: CAR REPLACEMENT

- At each time step, households decide whether they require to replace one of the vehicles they currently own, as a function of its age and the current length of ownership.

EV-ABM MODEL OVERVIEW



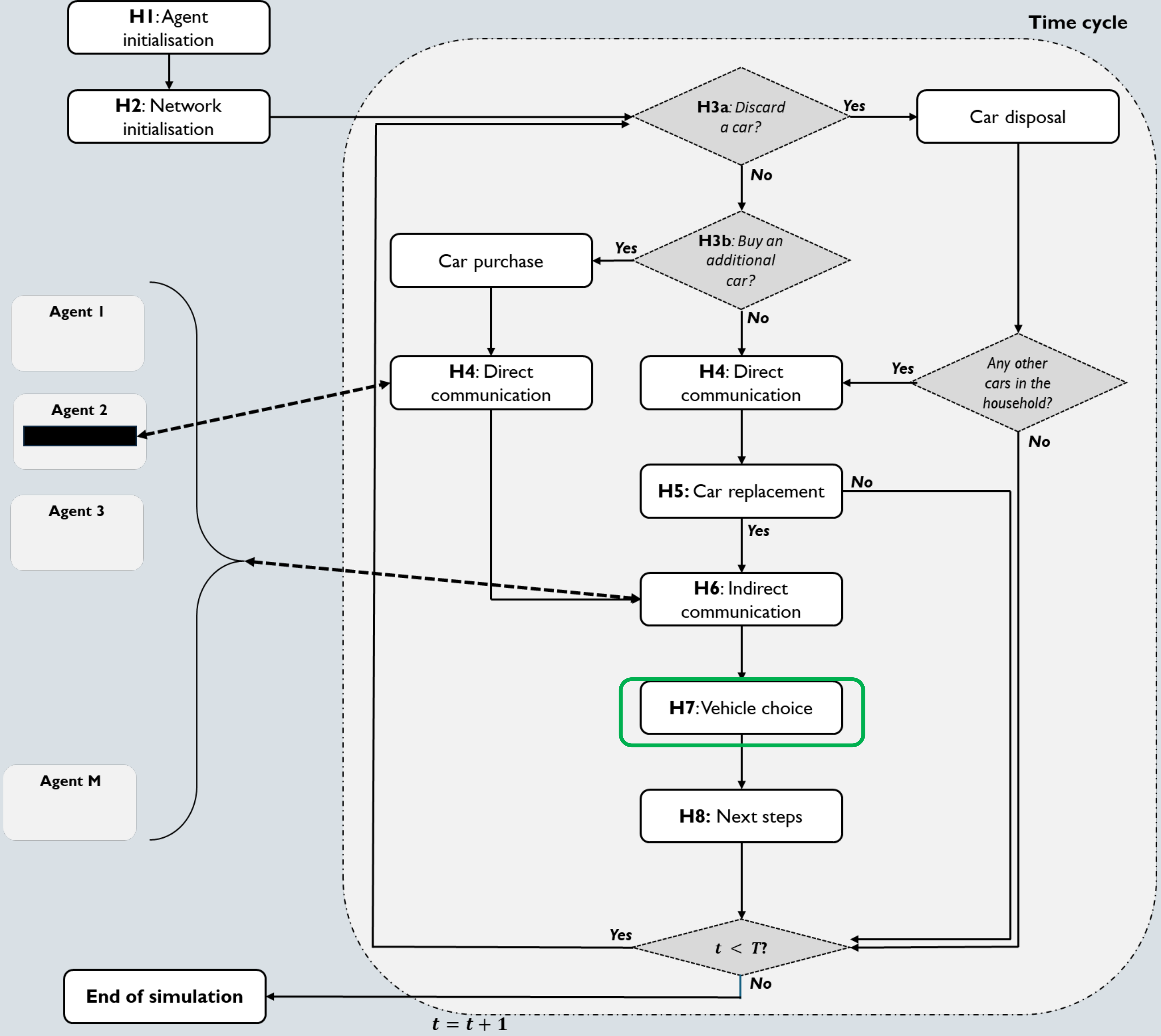
H6: INDIRECT COMMUNICATION

- Households observe the current adoption rates in their network to evaluate their willingness to consider the innovative alternatives (EV, HEV).
- **Willingness-to-consider** (WtC, adapted from Struben and Sterman, 2008) is a parameter assumed to deflect choice probabilities at time t. The parameter reflects familiarity with each alternative.
- WtC_{iqt} has different values for each household q, fuel type i and time t:

Fuel type i	Household q	WtC_{iqt}
ICE (Petrol or Diesel)	For all households at all times t.	1
EV/HEVs	Household q has adopted an EV/HEV at time t.	1
	Household q has not adopted an EV/HEV at time t, but at least one neighbour has.	$\frac{1}{1+\exp\left(-\varepsilon_i \cdot \left(MS_{iqt} - w_i^*\right)\right)}$
	Household q has not adopted an EV/HEV at time t, and no neighbour has.	0

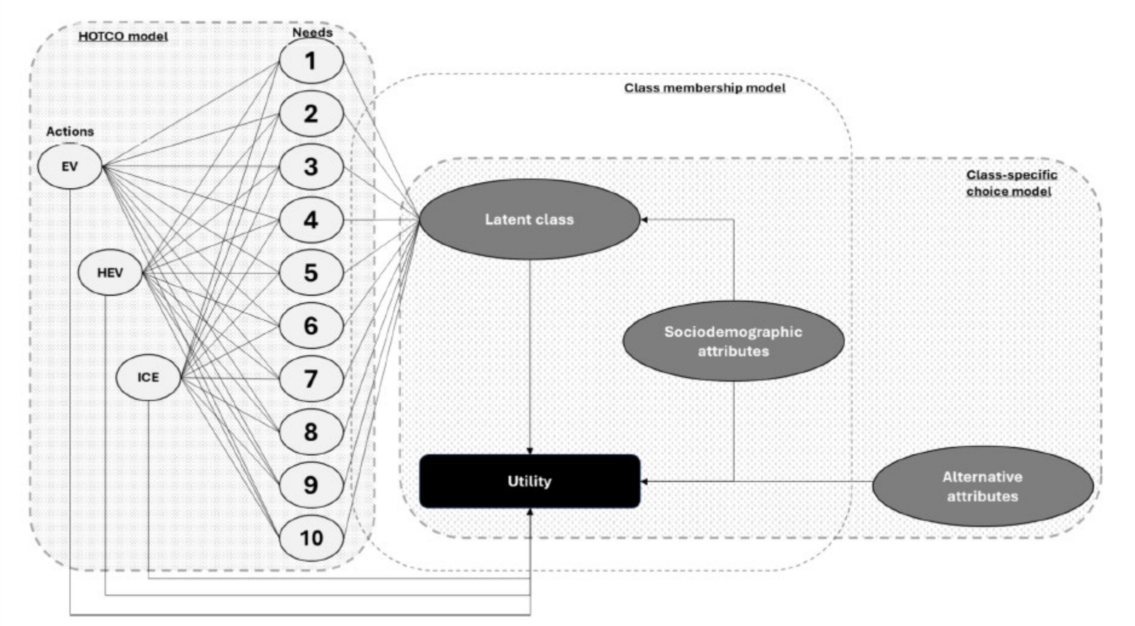
- MS_{iqt}, $i \in \{EV, HEV\}$: local level of adoption of fuel type i in the social network of household q at time step t.
- ε_i and w_i^*: calibration parameters.

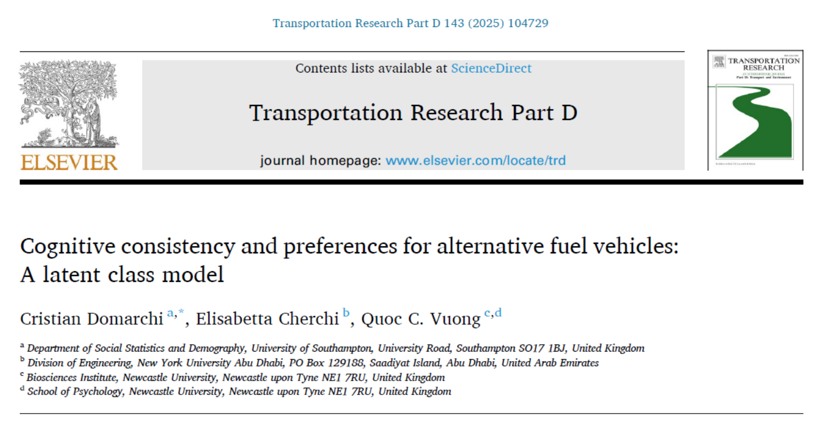
EV-ABM MODEL OVERVIEW



H7: FUEL TYPE CHOICE

- Finally, households **choose** a specific fuel type among the alternatives available in the market.
- We model this process using a **latent class-choice model** that includes cognitive consistency effects:





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Cognitive consistency and preferences for alternative fuel vehicles: A latent class model

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H7: FUEL TYPE CHOICE

- We model the probability that household q belonging to class s chooses fuel type i at time t with the following expression:

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

- The θ_{iqks} parameters come from the LCCM.
- Values of the X_{iqkt} attributes are different for each forecasting scenario.

BASE CASE SCENARIO: 1) CALIBRATION

- We defined a **base case scenario** for parameter calibration and generate forecasts assuming that, for the 2023–2050 period, all the variables evolve following a similar trend as in the 2019–2022 period.
- We calibrate parameters ε_i and w_i^* by running the model for the 2021–2023 period, for a grid consisting of the following parameters:

Parameter	Parameter value	Calibrated values
ε_{EV}	8.5, 11.5, 14.0, 17.0, 20.0	20.0
w_{EV}^*	0.005, 0.01, 0.05, 0.1, 0.3, 0.4, 0.5, 0.6, 0.8	0.01
ε_{HEV}	5.5, 7.5, 9.0, 11.0, 13.0	5.5
w_{HEV}^*	0.005, 0.01, 0.05, 0.1, 0.3, 0.4, 0.5, 0.6, 0.8	0.3

- We choose the combination of parameters that yields the minimum mean absolute error in predicting EV and HEV shares: 1.2% and 1.9%, respectively.
- We run the model multiple times per scenario, allowing each parameter to vary around its calibrated value. We construct a parameter grid assigning three values to each parameter: its calibrated value and variations of $\pm$5%. This approach generates prediction intervals for both vehicle sales and shares in each scenario.

BASE CASE SCENARIO: 2) SENSITIVITY ANALYSIS

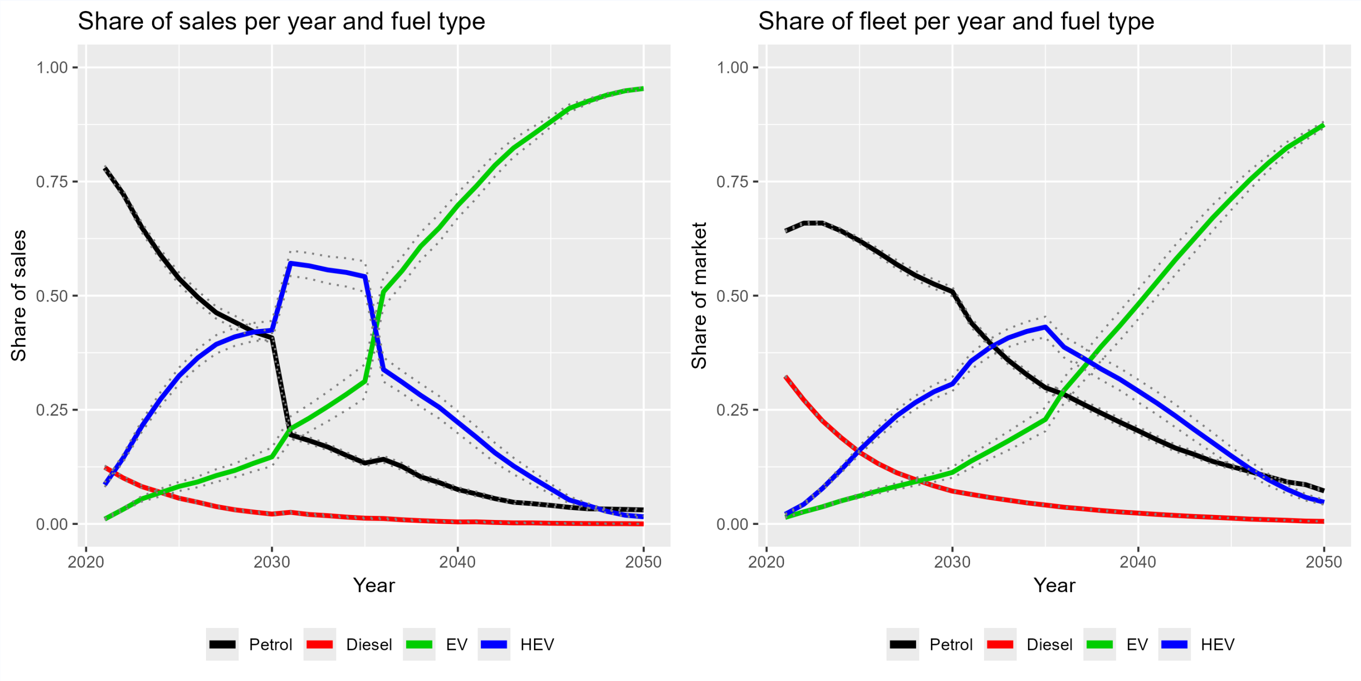
- Four additional parameter values in the model were set using reference values from the literature.
- To test their influence in the results, we conducted a sensitivity analysis by varying their values, running the model and comparing the forecasts obtained with the base case scenario:

Variable	Step	Set Value	Tested Value	Variation (%)	Mean absolute error (MAE, %) EV Sales	HEV Sales	EV Fleet	HEV Fleet	Diff. EV Sales (%)	Diff. Total Sales (%)
Minimum number of links	H2	3	1	-67	2.0	1.6	0.7	0.7	+0.7	+1.4
			5	+67	2.2	2.0	0.9	0.9	+1.0	+1.2
Maximum number of links	H2	40	20	-50	2.1	1.8	0.7	0.8	-1.6	+0.9
			60	+50	2.3	2.5	0.7	0.9	+0.5	+0.9
Maximum radius of homophily network	H2	$\frac{VDT}{4}$	$\frac{3VDT}{8}$	+50	3.1	2.1	1.0	1.0	-0.3	+0.4
			$\frac{VDT}{8}$	-50	3.2	4.4	1.8	3.3	-2.6	+0.8
Standard deviation of the WtC distribution	H6	$\frac{WtC}{4}$	$\frac{WtC}{8}$	-50	2.3	2.0	1.1	1.0	+1.6	+0.7
			$\frac{3WtC}{8}$	+50	2.5	2.1	0.8	1.3	+3.0	+3.8

- The model delivers relatively stable results even if these parameters are changed, which evidences the robustness of its forecasts.

BASE CASE SCENARIO: 3) FORECAST

- We assume that:
  - Sales of new Petrol and Diesel vehicles will stop in 2030.
  - Sales of new HEVs will stop in 2035.



- Under this scenario, EV shares will reach around 16% in 2030, and 80% in 2050.
- While the share will reach around 89% by 2050, the evolution will be slower than expected.

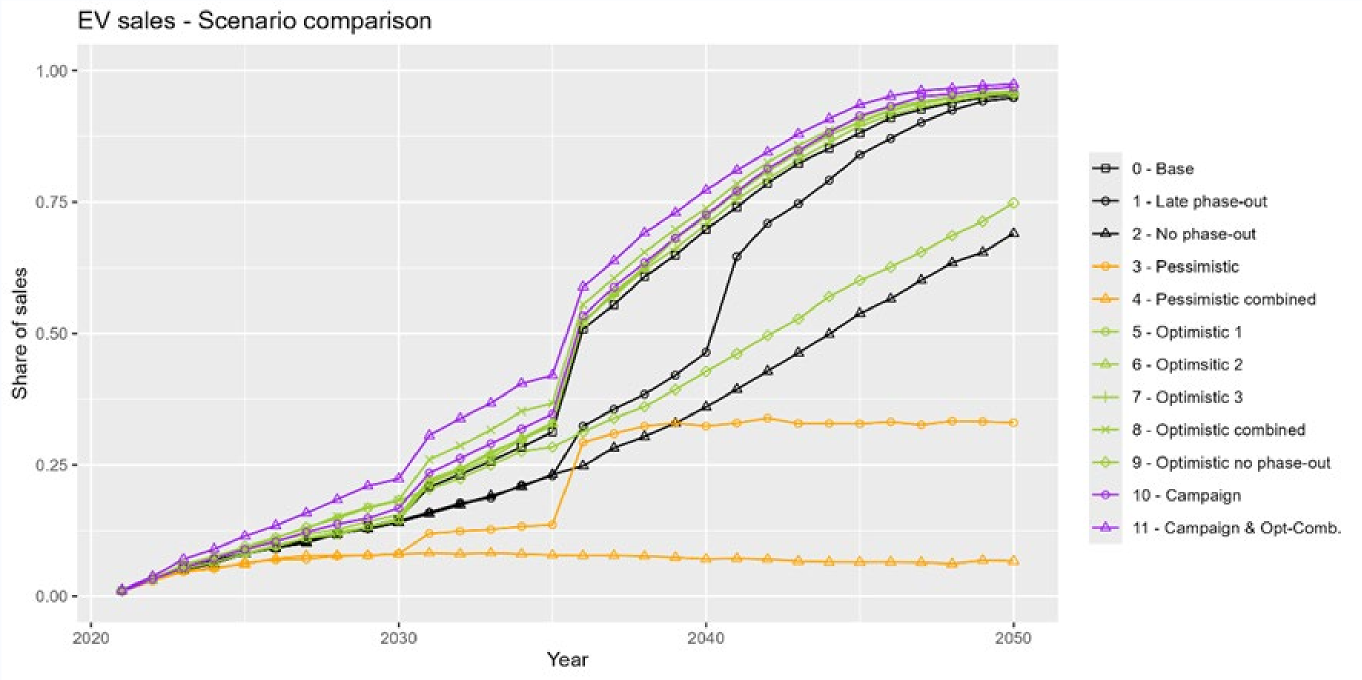
POLICY SCENARIOS: FORECASTING

- We define the following policy scenarios:

Scenario	Name	Definition
0	Base	–
1	Late phase-out	ICE/HEV phase-out will be postponed by 5 years
2	No phase-out	ICE/HEV phase-out will not happen.
3	Pessimistic	Market conditions will not continue improving over time.
4	Pessimistic – Combined	Scenario 2 + Scenario 3
5	Optimistic 1	Purchase grants are implemented.
6	Optimistic 2	Support network for EVs is improved.
7	Optimistic 3	Energy costs are reduced.
8	Optimistic – Combined	Scenario 5 + Scenario 6 + Scenario 7
9	Optimistic – Combined, No phase-out	Scenario 8 + Scenario 2
10	Campaign	Aggressive advertisement campaign aiming at promoting EVs.
11	Campaign, Optimistic – Combined	Upper bound for forecasts, most favourable conditions.

POLICY SCENARIOS: RESULTS

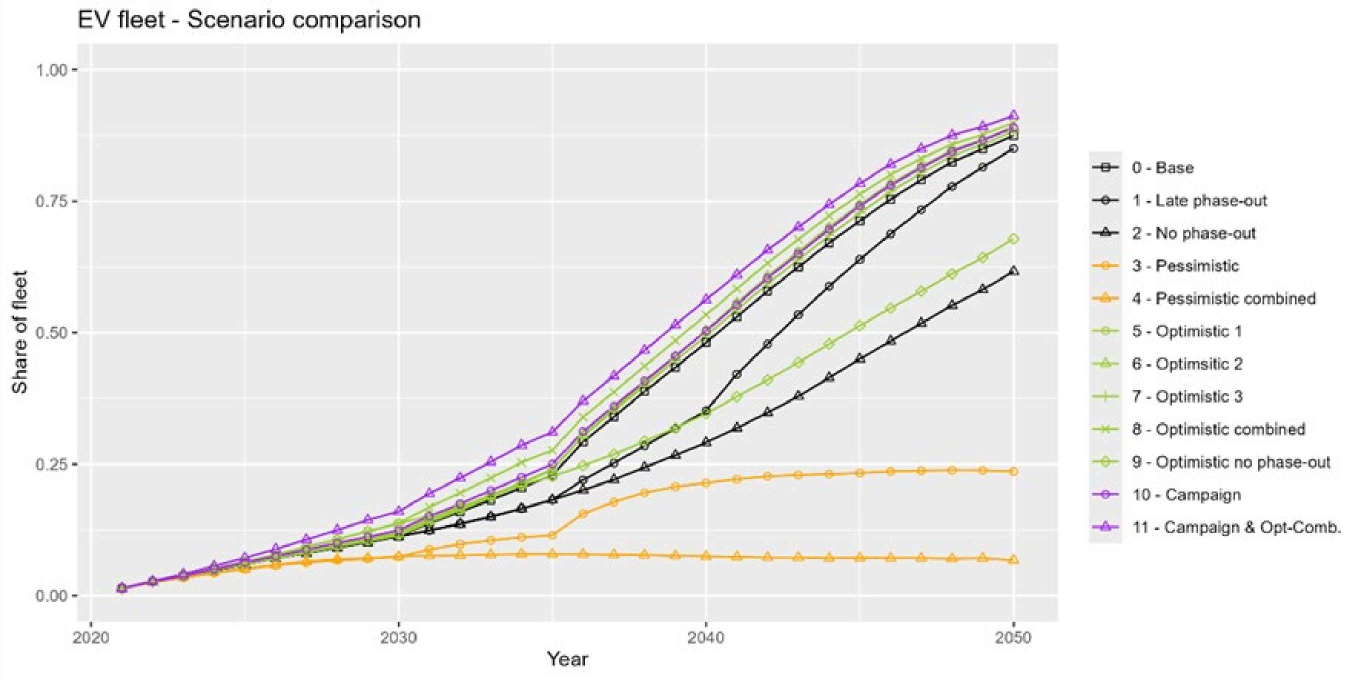
- Our models obtain the following results:



- Pessimistic scenarios generate significantly lower EV shares over time.
- The optimistic scenarios perform similarly compared to the base case scenario at the beginning and end of the simulation; however, sales improvements can be achieved earlier.
- ICE/HEV phase-out dates are key: even the optimistic scenario performs badly if phase-out is not implemented.

POLICY SCENARIOS: RESULTS

- Our models obtain the following results:



- No scenario achieves the 46% EV shares required to fulfil the UK 2030 climate change goals.
- “Combined” optimistic measures should be considered.
- Communication campaign can be highly effective.

CONCLUSIONS

- The model simultaneously tackles household-level decision-making (**substitution**) and network-level **diffusion** of EVs.
- The modelling method integrates behavioural and instrumental effects by considering the following effects:
  - Preference heterogeneity, using a latent class-choice model as the agent decision rule
  - Influence of attitudes and emotional appraisals, using the HOTCO model
  - Direct communication between agents, also modelled with HOTCO
  - Indirect communication in the social network, using willingness-to-consider
  - Changes in car ownership level during the simulation period

CONCLUSIONS

- The model forecasts highlight:
  - The importance of combining “hard” policy measures (including forbidding the sales of ICE cars and HEVs), with “soft” policies including awareness campaigns
  - At the current trends of diffusion, EVs will not reach a sufficient market share to reduce transport carbon emissions in the UK by 2030 by the required levels
  - Postponing the phase-out of ICE cars and HEVs can significantly compromise EV diffusion over time

YOUR QUESTIONS