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A systematic review of the agent-based modelling/simulation paradigm in mobility transition

Milad Mehdizadeh *, Trond Nordfjaern, Christian A. Klöckner

Norwegian University of Science and Technology (NTNU), Trondheim, Norway

A R T I C L E I N F O

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A B S T R A C T

Simulations and agent-based modelling (ABM) have gained momentum as techniques in the transport, energy, and technology diffusion literature to analyse the mobility transition as a complex emergent phenomenon. This study systematically reviews the application of the ABM paradigm in 86 mobility transition studies. The study reveals several research gaps and proposes avenues for future research. Our review highlights that (i) the field has considerably matured in studying the diffusion of electric vehicles, (ii) both price-based and preference-based scenarios for mobility transition should be considered in future research, (iii) most of the empirical model calibrations have been confined to Western countries. Not only will the literature benefit from similar research in other Western regions, but also from non-Western nations with their unique mobility transition pathways, (iv) the conceptual modelling framework of studies can be divided into the two categories of theory-driven and heuristic models. The theory-driven models, which include psychological and non-psychological (e.g., activity-based travel) models, tend to use well-established behavioural rules, (v) most of the models have used the random utility maximization concept, social psychological models, and other simple assumptions/thresholds for the decision-making process of agents, (vi) half of the studies did not validate their models, and (vii) two-thirds of studies omitted to discuss interaction topology among agents. Major remaining challenges and gaps are identified in the review.

1. Introduction

The term "mobility transition" refers to any kind of transition from traditional mobility patterns and options to innovative and sustainable mobility options (Köhler et al., 2009; Docherty et al., 2018; Fagnant and Kockelman, 2015). There is a growing focus on decarbonisation of the transport system through diffusion and adoption of Electric Vehicles (EVs), alternative fuel vehicles (e.g., hydrogen cars), micro-mobility (e.g., electric bicycles and scooters), mobility services (e.g., car sharing, bike sharing, bus services), shared automated vehicles, and changes in charging and refuelling behaviour. Such mobility transitions are not only influenced by policies and economic conditions, but also by social influences, beliefs about costs and benefits related to factors going beyond mere economic factors, such as habits and routines, cultures that develop over time, and lock-in situations created by earlier decisions. This complexity and especially the dynamics and heterogeneity of consumer engagement are hard to capture with ordinary behaviour studies (e.g., surveys, observational studies or experiments alone) and analyses (e.g., system dynamic, discrete choice models, regression).

The transport sector constitutes a major global sustainability challenge. For instance, transport accounts for around 30 % of the total CO_2 emissions in the EU, leaving 43 % to passenger vehicles (Fevang et al., 2021). Reaching emission targets requires a transition to zero or low emission transport. Recent efforts have been made to improve mobility transition policies through electrification and automatisation of conventional vehicles, promoting low-carbon options, and facilitation of shared mobility services to deal with environmental and safety issues as well as inefficiencies of conventional transportation systems (Docherty et al., 2018; Fagnant and Kockelman, 2015). In terms of electrification, many developed countries have increased the sale and uptake of electric vehicles. In Norway, for instance, the sale of electric vehicles has grown rapidly from 229 units in 2000 to 10,434 in 2013 as a leading nation in the area (Mersky et al., 2016). In 2020, 52.2 % of newly registered cars in Norway were battery electric vehicles, and 20.4 % were plug-in hybrids (Fevang et al., 2021). Such mobility transitions, however, are currently in progress and will be vigorously pursued in the future. Although such rapid changes in technology from the supply side are expected, little is known about how individuals adjust to such changes in

* Corresponding author at: Norwegian University of Science and Technology (NTNU), Bygg 12, 579, Dragvoll, Trondheim, Norway.
E-mail address: milad.mehdizadeh@ntnu.no (M. Mehdizadeh).

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mobility from the demand side. Additionally, it is unclear how the state-of-the-art advanced simulation techniques have captured such mobility transitions and social changes.

A technique more and more frequently used to study mobility transitions is to dynamically simulate different agents' (e.g., consumers, citizens, governmental agencies, manufacturers, vehicles, fuel stations) behaviour by Agent-Based Models (ABM). ABM has been applied in a wide range of scientific fields, such as innovation diffusion, agricultural innovations, marketing, energy technology adoption, transport, social science, economy, healthcare provision, water-saving innovations, mobile phones, and smart metering (Köhler et al., 2009). The use of ABMs has also been gaining momentum in the transport, energy, and technology literature to model complex emergent phenomena such as mobility choices. But why is an ABM an interesting tool for modelling the diffusion and adoption of mobility innovations? An ABM is a bottom-up approach that captures individual behaviour at the micro-level and forecasts the emergent behaviour (e.g., diffusion or transition) at the macro-level (Kiesling et al., 2012). Adoption behaviour has a non-linear nature and linear models are not well-suited to capture such behaviours. Diffusion is not only a rational economic process, but also a complex system including heterogeneous decision-makers (agents), different personal tastes, word of mouth impacts, social network influences, temporal and spatial effects and learning processes from experiences. An ABM can provide a straightforward framework for simulating and thereby evaluating such complex decision systems considering a heterogeneous population, an evolving number of parameters, social interactions, and interconnection of agents with each other in a dynamic process. Most technological progress and developments are currently unclear to the general public and may also be rapidly changed by governmental agencies and industries in the future. In addition, most people have no good knowledge about different aspects of mobility innovations at an early introduction phase and they may be confronted with a situation in which several acquaintances encourage them to adopt such mobility options in the future. Therefore, many analytical techniques and cross-sectional studies cannot capture different scenarios related to technological progress over time. A social simulation (i.e., ABM) can cope with the dynamic nature and non-linear development of technology transition in the transport system.

Different types of methods have been used in other research strands tackling mobility transition to explain or predict modal shifts to sustainable transportation options. In addition to ABM studies, other research has utilised statistical models (e.g., regression models), structural equation models (Klöckner, 2014; Simsekoglu and Klöckner, 2019), discrete choice models (e.g., binary logit, multinomial logit, nested logit, mixed logit, and hybrid choice models) (e.g., Liao et al., 2017; Dias et al., 2017), and system dynamic models (e.g., Linder, 2011; Ardilaa and Francob, 2013). Statistical analyses and econometric models (e.g., choice models) provide information about modal choices and preferences based on statistical relationships. However, they cannot reveal the dynamics behind these choices and preferences. Mobility is an adaptive and dynamic system with numerous actors pursuing different goals. ABMs can, however, consider the dynamic nature of the transition at larger spatial and temporal scales. Unlike econometric methods such as choice models, which fail to capture non-linear systems and evolving features that characterise mobility and behavioural change, ABM is a flexible approach suited to capture this complexity. Additionally, ABMs are capable of accounting for the interactions between agents and environments, while statistical models do not. Furthermore, system dynamics models, a top-down approach, depict the aggregate system in terms of stocks and flows rather than disaggregated parts of a system described by ABMs. In contrast, ABM, which is a bottom-up approach, can reproduce heterogeneous mobility decisions made by individuals (agents). Due to this, ABM can overcome many of the shortcomings of the cited models when reproducing mobility systems in the future.

The main aim of this study is to review the existing knowledge of the application of ABM on mobility transition research questions. We (i) describe the state-of-the-art in the field, (ii) identify main research gaps, and (iii) show avenues for future research. A closer look at the literature reveals that little is known about the following questions:

- To what extent have different aspects of mobility transitions been simulated?
- How is the geographical distribution of case studies?
- How are conceptual modelling frameworks developed?
- What is the main decision-making process of agents?
- How are models calibrated and validated?
- What is the interaction topology (social network) between agents in ABMs?

In this literature review, we systematically analyse the agent-based modelling and simulation technique used in 86 mobility transition studies and thereby address the abovementioned research questions. We found two papers which to some extent reviewed studies that investigated urban mobility using agent-based models (Li et al., 2021; Maggi and Vallino, 2016). Maggi and Vallino (2016) provided a critical review of studies of agent-based modelling of urban freight and passenger mobility. However, they only focused on eight papers concerning urban passenger mobility and their review emphasised the current travel demand or traffic simulation issues. Moreover, Li et al. (2021) recently summarised research on agent-based modelling of the influence of autonomous vehicles on city logistics and urban mobility. This review also focused on the operational and network nature of mobility, however, neither of the two reviews targeted studies on consumer behaviour nor other kinds of mobility transition perspectives.

On the technical side, there is little knowledge about: (i) what aspects of the mobility transition have been simulated so far, (ii) which regions are pioneers in the application of ABMs for emerging mobility options, (iii) what are the common conceptual modelling frameworks of such ABMs, and (iv) how social network of agents is assumed in mobility transition studies. Our review addresses these research gaps and adds the following to the current knowledge of simulation of mobility transition: (i) it yields new insights into researchers' and policymakers' perspectives about different kinds of transitions in mobility systems. The field has had great success in simulating EV diffusion. However, little is known about to what extent other kinds of mobility innovations are simulated through ABM. We classify studies based on a conceptual clustering, (ii) it provides a road map for developing a straightforward and conceptual agent-based model about mobility issues, and (iii) the study can help to better understand how ABMs are developed based on existing data.

The remainder of the paper is organised as follows. Section 2 describes the review methodology that we used to select 86 candidate publications. Section 3 summarises key statistics of the selected publications. The different research questions of the study are addressed in Section 4. Finally, we represent concluding remarks and future research directions in Section 5.

2. Research approach

We employed a systematic review technique to identify relevant original research papers and sources. We followed recommendations published by several scholars (e.g., Wee and Banister, 2016) to decide how to include or exclude different references in the literature review process. Both peer-reviewed and non-peer-reviewed materials, such as research reports, were included in the screening process. First, several different combinations of keywords were selected to be electronically searched in three well-known academic search engines, i.e., Google Scholar, Scopus and Web of Science. Using different spellings, tenses, and word variations, as well as synonyms, we found all the relevant keywords for the topic. A variety of approaches were used to locate these keywords including background reading, dictionaries, regular and database thesauri, subject headings, and text mining tools. Our search also led us to discover new keywords. As illustrated in Fig. 1, a two-part keyword search was applied to identify papers that utilised an agent-based modelling approach in the analysis of mobility transition. As for the first part of the keywords, the following terms have been used: "*transportation transition*", "*transport transition*", "*mobility transition*", "*modal shift*", "*hybrid and electric vehicle*", "*automated mobility*", "*autonomous vehicle*", "*sustainable mobility*", "*sustainable transport*", "*passenger transport*", "*adoption of EV*", "*diffusion of EV*", "*mobility service*", "*mobility policies*", "*transport policies*", "*transport energy demand*", "*urban mobility*", "*transportation investment*", "*transportation technology*", "*mode choice*", "*refuelling behaviour*", "*mobility + citizen engagement*", "*mobility + lock-in*". Since many interchangeable terms such as "mobility", "transportation", and "transport", have been used in the literature, we included all of them in the search. We also searched for "*agent-based model*"[1] in the second part of the keywords. The Boolean operator "+" connected the two parts of the keywords.[2]

The electronic search was conducted during August 2021 and papers published after August 2021 are not included in this review. As expected, this electronic search resulted in thousands of sources including journal articles, conference papers, master and doctoral theses, department reports etc. First of all, we scaled down the initial results (>100 k) based on article titles. If titles could not be used to determine the relevance of these initial results, we screened the abstracts. By this approach, we ended up with about 300 relevant results. After reading the full text of these sources, we reduced them to 77 sources. To detect eligible studies which were not embraced by our general search, we also used a snowball approach to reveal remaining resources in which were either directly cited or were cited by a paper in our initial list. This snowball search led to nine new references. Finally, a total of 86 resources were chosen from the pool of studies for the meticulous review. To avoid duplication of references, we used EndNote 20.

To screen and evaluate the eligibility of studies to be included or excluded in the final version of the literature review, the following criteria have been used (see also Fig. 1). Firstly, we only focused on papers published in English. Secondly, journal papers were preferred for the main review to increase the scientific quality of work. However, some dissertations, book chapters and project reports were also included if they were considered of high quality and high relevance for the topic. Thirdly, we were looking for papers that investigated urban passenger mobility transition through employing the agent-based modelling paradigm. We excluded research papers dealing with traffic simulations, traditional travel demand modelling, city logistics and parking search models using agent-based models. According to our research aims and questions, we only targeted research papers that studied the complex and dynamic nature of different decision-making processes influencing any transition or shift to more sustainable transport modes through developing an agent-based simulation approach. Even though we also found a few other relevant papers to our literature review these were excluded because they had not reported enough information about the ABM modelling process, input data and calibration methods.

3. Results

3.1. Review statistics

As shown in Table A (Appendix A), 77 papers (around 90 %) out of 86 final resources are journal articles and the remaining are either theses, book chapters, or project reports. A total of 23 papers (around 27 %) were published in the five following journals: *Transportation Research Part A*: *Policy and Practice*, *Energy Policy*, *Technological Forecasting and Social Change*, *Transportation Research Part C*: *Emerging Technologies*, *Energies*. The journals have a combination theme of transport, energy, technology, environment, psychology, and computer science.

Looking at Fig. 2, it is evident that about 76 % of sources are published after 2014. We expect an increasing rate of publications soon due to the emergence of several kinds of mobility innovations and more diffusion of ABM.

3.2. Review results

In Appendix B, Table gives an overview of all selected papers, listing their key characteristics. We evaluated the papers' focus (which aspect of the mobility transition was addressed), the main variables used in the model, scenario developments, region of study, target agent or population, the concept behind the developed model, the main decision-making processes utilised by agents in the model, model parameterisation or calibration data and method, the simulation time horizon, validation methods, and interaction topology (the way of agents connected with each other). We synthesise each of these aspects in this section.

3.2.1. Aim of the studies or aspect of the mobility transition addressed

Out of 86 papers, 43 studies (50 %) exclusively focussed on the diffusion of EVs. The main aim of these studies was to investigate EVs market share penetration from different perspectives: (i) user behaviour and social aspects (e.g., Lee and Brown, 2021a, 2021b; Pagani et al., 2019), (ii) the effects of different policies (e.g., Huang et al., 2021; Querini and Benetto, 2014), (iii) charging technology/demand and battery capacities (e.g., Zhuge et al., 2021; Rodemann et al., 2019), (iv) manufacturers impact (e.g., Vouzavalis, 2020; Kieckhäfer et al., 2017), and (v) willingness of purchasing/using of EVs (e.g., Klein et al., 2020; Ning et al., 2019).

The second half of the papers simulated other aspects of the mobility transition: (i) Automated Mobility on-Demand (AMoD) (e.g., Oh et al., 2020; Basu et al., 2018), (ii) modal shift to sustainable transport modes (e.g., Maggi and Vallino, 2021; Faboya et al., 2020), (iii) different shared mobility services such as carsharing, ridesharing, bike-sharing, shared taxi, carpooling (e.g., Inturri et al., 2019; Fagnant and Kockelman, 2014), and (iv) alternative fuel vehicles such as hydrogen fuel vehicles or natural gas vehicles (e.g., Sopha et al., 2017; Vliet et al., 2010). The aims (type of mobility transition) of the studies are also classified in more detail in Table 1.

3.2.2. Variables embedded in the ABMs

According to the employed data and developed ABMs, the studies have implemented different types of variables on disaggregated and aggregated levels. Some studies also considered virtual distribution functions for variables instead of directly measuring them through recorded data or self-reported methods. Generally speaking, the following categories of variables have been embedded in the ABMs in

[1] We also used alternative terms such as "agent", "agent-based simulation", "simulation", "computational model", "multi-agent models", etc. As these alternative searches led to similar resources, we did not mention these alternative keywords in the manuscript. We believe the main reason why the results of such alternative keywords are identical (when searching for "agent-based model") is that even if a paper uses another term like "computational model" consistently, some terms like "agent" or "agent-based model" can be found in the reference list of that paper.

[2] The number of results shown in Fig 1 is based on the search of keywords without using the quotation mark ("X"), i.e., X + X. In our initial search, we did not want to limit the results to the exact words given in our keywords. It is important to note that we also searched for these keywords using the exact words of the search terms (i.e., "X" + "X"). The results of these two searches showed that by restricting our search with quotation marks we could miss some relevant papers that have used other terms or keywords. This is why we finally used the first method (without the quotation mark). We have also considered all variations of keywords such as British and American spellings and agent-based, with or without the dash (–). Further, the number of results was the maximum number of results among three electronic search engines, in which Google scholar mostly had the highest number of results because it covered results of the other two search engines as well.

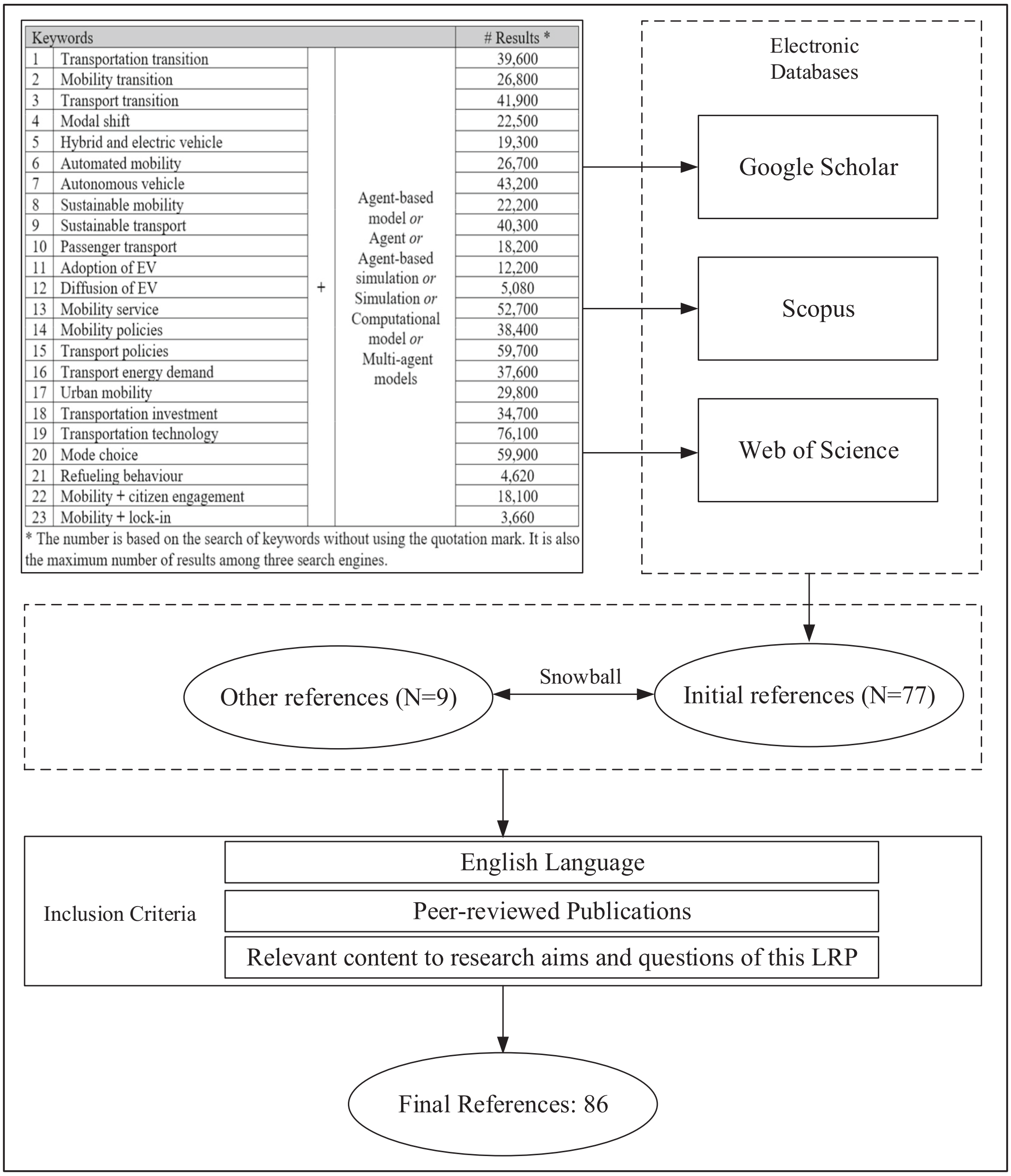

Fig. 1. The review procedure.

mobility transition research: (i) demographic and socioeconomic characteristics on individual and household levels, (ii) vehicle-related attributes such as vehicle price and usage, (iii) social influence and environmental attitudes, (iv) charging profiles (e.g., charging speed), (v) home charging, (vi) fuel-related attributes such as battery size, fuel price, (vii) spatial factors (e.g., residential location), and (viii) driving profiles (e.g., travel distance and frequency).

3.2.3. *Policy scenario developments*

A total of 81 studies (94 % of the studies) developed different scenarios and the remaining five papers only simulated the business-as-usual situation. Most of the scenarios have been developed to investigate the effects of different variants of the following policies: (i) price-based scenarios such as changing vehicle price, government subsidies, petrol and electricity prices, taxes, incentives, (ii) preference-based scenarios i.e., psychological changes such as changing satisfaction or preferences, (iii) charging-related scenarios such as technological progress and fast-charging, (iv) changing social network patterns, (v) expansion of sustainable transport infrastructures, (vi) different system operations (e.g., different seat capacities of public transit and demand rates), (vii) introducing new shared mobility options and disincentives for using private petrol cars.

3.2.4. *Region of study*

Concerning the place of the case studies, around 58 % of the research has been confined to European countries. As illustrated in Fig. 3, the US, with 18.60 %, has the highest share of conducted studies among the countries in the world. The Netherlands (12.79 %), Germany (11.63 %), China (8.14 %), Switzerland (6.98 %) and the UK (5.81 %) follow in terms of the number of mobility transition publications employing ABM. Looking at the Figure in Appendix C, it is evident that most studies have been conducted in western nations. However, it seems that there is less attention given to the application of the ABM paradigm in mobility transition studies in Canada, Australia, New Zealand, Japan, Africa, and many countries in Western Asia and South America.

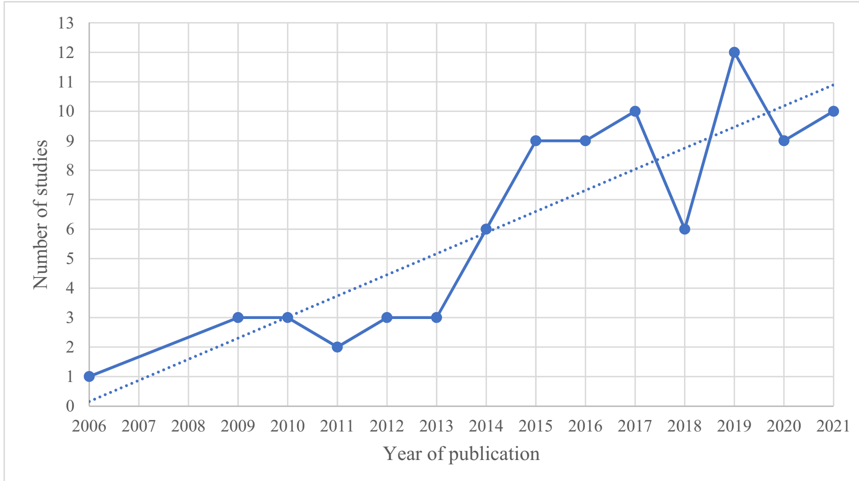

Fig. 2. Trend of publications.

3.2.5. *Target agent or population*

As for target agents or populations, studies can be categorised into two research streams. The first stream has only focussed on one single type of agents throughout the agent-based modelling process. The second stream has considered multiple types of agents. A total of 45 studies (52 %) targeted single agents such as individuals, households, drivers, travellers, vehicles, new car buyers, inhabitants, zip codes. On the other hand, the remaining research papers defined several different types of agents in the ABM. For instance, Klein et al. (2020) considered consumers, vehicles and producers as three independent agents in the modelling process. Geerlings (2020) used two independent agent types: EVs and charging points. Segui-Gasco et al. (2019) defined travellers and operators as agents in the simulation algorithm.

3.2.6. *Conceptual frameworks of the model*

In agent-based models, studies need to shape a conceptual framework to illustrate how a model homogenously or heterogeneously can be shaped based on a set of behavioural rules. Some of the most frequently used conceptual frameworks are shown in Fig. 4. Concerning the conceptual modelling framework of studies, we can divide the state of the art into two categories: theory-driven and heuristic models.

Theory-driven frameworks are those that use reasoning about relations to bring about behavioural rules, such as psychological models (e.g., theory of planned behaviour, diffusion of innovation) and activities-based models. Fifty percent of the analysed studies ($n = 43$) have utilised either a psychological or a transportation planning conceptual framework to formalise their ABM's decision rules. Within this category, models are referring to different psychological theories or theories inspired by psychological research such as Roger's Diffusion of Innovation Theory, the Bass model,[3] the Consumat framework, the Theory of Planned Behaviour, the Fisher and Pry diffusion model, or innovation diffusion driven by changing mindsets (InnoMind). According to Roger's Diffusion of Innovation (DOI) theory (Rogers, 2010), consumers adopt innovations (e.g., EVs) based on attributes of the innovation (e.g., relative advantage, complexity, or compatibility) and attributes of the adopters (e.g., social connectedness, knowledge, resources). In contrast to the Bass model (Bass, 1969), which assumes that consumers are homogeneous in decision making, the DOI theory considers the heterogeneity of consumers within a population. The Bass model presumes that adopters solely follow the mass media as a source of information, whereas the DOI addresses social status, risk tolerance and attachment to social networks at an individual level. Akin to the level of innovativeness, the DOI theory divides adopters into the five following groups, separated by the time of adoption: 2.5 % innovators who adopt the innovation first, 13.5 % early adopters who follow the innovators, 34 % form the early majority, 34 % form the late majority, and 16 % are referred to as laggards. Like the DOI, Fisher and Pry's model suggests an S-curve pattern for the diffusion of innovation (Fisher and Pry, 1971). This model fits for innovations that do not require noticeable behavioural changes. Although the DOI theory can divide adopters into different categories, the Theory of planned behaviour (TPB) has more nuances, which, allows understanding how and to what extent behavioural beliefs can explain an agent's decision to adopt (or reject) an innovation. Employing the TPB (Ajzen, 1991), some studies assumed that a transition behaviour to more sustainable mobility options is a result of an individual's behavioural intention, while the intentions are shaped by attitudes, subjective norms, and perceived behavioural control. In the TPB, while attitude refers to a favourable or unfavourable evaluation of behaviour, subjective norm refers to a perception from significant others (e.g., friends, family members, peers) to conduct or not to conduct a specific behaviour. Perceived behavioural control also refers to the perceived ease or difficulty of conducting a behaviour. Wolf et al. (2015) developed the "Innovation diffusion driven by changing minds" (*InnoMind*) theory which is a more general multi-level mechanism studying belief change with localist neural networks. The *InnoMind* model overcomes some limitations of cited psychological ABM (e.g., developed via the TPB), incorporating the role of emotion in decision-making and communication.

The remaining theory-driven approaches have employed activity-based models, in which, mobility is regarded as a derived demand of individuals from the need to conduct daily activities (e.g., shopping, work) (Pinjari and Bhat, 2011). The activity-based travel demand model belongs to the third generation of travel demand models, which has the capability to consider heterogeneous travel-related decisions at a disaggregate level, such as activity participation, activity durations, activity locations, mode/departure-time/route choices, as well as transport network and operation features (de Dios Ortúzar and Willumsen, 2011). Along with agent-based simulation, this model allows developing many transport-related scenarios, investigating how emerging mobility options can change activity-travel patterns of individuals. For instance, several ABMs such as SimMobility (Oke et al., 2020; Oh et al., 2020), MATSim (Liu et al., 2017; Hörl et al., 2021; Segui-Gasco et al., 2019; Ciari et al., 2016; Novosel et al., 2015), IMSim (Segui-Gasco et al., 2019), and SelfSim-EV (e.g., Zhuge et al., 2020a, 2020b) are developed via the concept of activity-based theory.

The other half of the studies we analysed has used a heuristic

[3] Roger's DOI and the Bass model are not related directly with psychological theories.

Table 1
Type of mobility transition in ABM studies.

No.	Study	EV	Alternative fuel	Modal shift	Shared mobility	Carsharing	Ridesharing	Bikesharing	Carpooling	Shared taxi	Automated vehicle
1	Adepetu and Keshav, 2017	✓									
2	Adepetu et al., 2016	✓									
3	Ahanchian et al., 2019			✓							
4	Ahkamiraad and Wang, 2018	✓									
5	Arian and Chiu, 2017			✓							
6	Aziz et al., 2018			✓							
7	Basu et al., 2018										✓
8	Brown, 2013	✓									
9	Buchmann et al., 2021	✓									
10	Bühne et al., 2015	✓									
11	Chaoxing, 2017	✓									
12	Chaudhari et al., 2019	✓									
13	Choi, 2016	✓	✓								
14	Ciari et al., 2016					✓					
15	de Haan et al., 2009		✓								
16	Eppstein et al., 2011	✓	✓								
17	Faboya et al., 2020			✓							
18	Fagnant and Kockelman, 2014				✓						✓
19	Geerlings, 2020	✓									
20	Gnann et al., 2015	✓									
21	Gnann et al., 2018	✓									
22	Hajinasab et al., 2016			✓							
23	Hörl et al., 2019										✓
24	Hörl et al., 2021										✓
25	Huang et al., 2021	✓									
26	Huétink et al., 2010		✓								
27	Hussain et al., 2016								✓		
28	Inturri et al., 2021				✓						
29	Inturri et al., 2019				✓						
30	Kangur et al., 2017	✓									
31	Kangur, 2014	✓									
32	Kieckhäfer et al., 2014	✓									
33	Kieckhäfer et al., 2017	✓									
34	Klein et al., 2020	✓									
35	Köhler et al., 2009		✓								
36	Köhler et al., 2020			✓							
37	Lemoine et al., 2016			✓							
38	Liu et al., 2017				✓						✓
39	Lu et al., 2018							✓			
40	Maggi and Vallino, 2021			✓							
41	Martinez and Viegas, 2017						✓				✓
42	Martinez et al., 2015									✓	
43	Martínez et al., 2016					✓					
44	McCoy and Lyons, 2014	✓									
45	Mueller and de Haan, 2009			✓							
46	Natalini and Bravo, 2013			✓							
47	Ning et al., 2019	✓									
48	Noori and Tatari, 2016	✓									
49	Novizayanti et al., 2021	✓									
50	Novosel et al., 2015		✓	✓							
51	Oh et al., 2020										✓
52	Oke et al., 2020										✓
53	Olivella-Rosell et al., 2015	✓									
54	Pagani et al., 2019	✓									
55	Querini and Benetto, 2015			✓							
56	Querini and Benetto, 2014	✓	✓								
57	Lee and Brown, 2021aa	✓									
58	Lee and Brown, 2021b	✓									
59	Ramsey et al., 2018	✓									
60	Rodemann et al., 2019	✓									
61	Schröder and Wolf, 2017					✓					
62	Schwoon, 2006		✓								

(*continued on next page*)

Table 1 (*continued*)

No.	Study	EV	Alternative fuel	Modal shift	Shared mobility	Carsharing	Ridesharing	Bikesharing	Carpooling	Shared taxi	Automated vehicle
63	Segui-Gasco et al., 2019						✓				
64	Shafiei et al., 2012	✓									
65	Shafiei et al., 2013			✓							
66	Shimizu et al., 2014							✓			
67	Shirzadi Babakan et al., 2015			✓							
68	Silvia and Krause, 2016	✓									
69	Sopha et al., 2017		✓								
70	Stephens, 2010	✓									
71	Sun et al., 2019	✓									
72	Sweda and Klabjan, 2015	✓									
73	Tran, 2012		✓	✓							
74	van der Kam et al., 2019	✓									
75	Vijayashankar, 2017	✓									
76	Vliet et al., 2010		✓								
77	Vooren and Alkemade, 2012		✓	✓							
78	Vouzavalis, 2020	✓									
79	Wolbertus et al., 2021	✓									
80	Wolf et al., 2015			✓							
81	Zhang et al., 2011		✓								
82	Zhuge et al., 2021	✓									
83	Zhuge et al., 2019a	✓									
84	Zhuge et al., 2019b	✓									
85	Zhuge et al., 2020a	✓									
86	Zhuge et al., 2020b	✓									

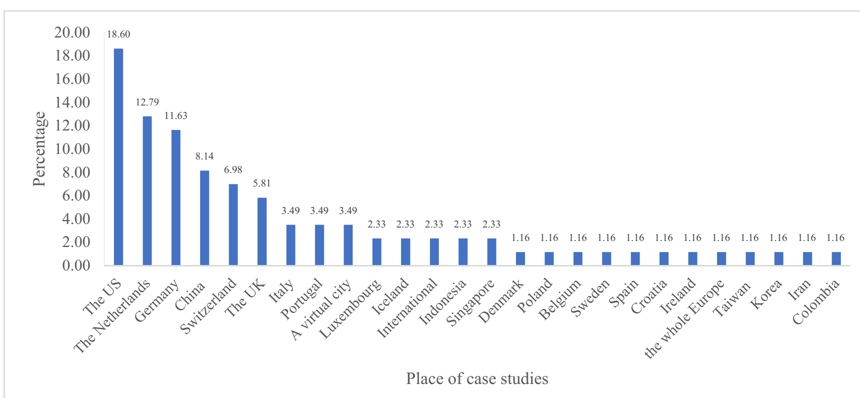

Fig. 3. Percentages of studies according to location of case studies.

algorithm or tool to form a behavioural rule for their ABM. We call their approach heuristic because (i) the relationships between agents-related variables and the internal flows in the model are not derived from a well-established theoretical framework, or (ii) such models are based on some simplified assumptions and thresholds and (iii) unlike theory-driven models, which are based on previous theories, heuristic models have a more exploratory nature. The conceptual modelling framework of some heuristic models is reviewed as follows.

Employing an actual dataset on charging patterns in Amsterdam, Wolbertus et al. (2021) developed an ABM to dynamically simulate how people choose a charging station. Considering the interaction of three agents (EV drivers, non-EV drivers, and the charging point operator), the model dynamically checks the selection process of a car (EV and non-EV), availability of a favourite charging station, and selection of connection time. Certain values were assumed for different parameters to shape the simulation iteration process of the model. For example, it was assumed that battery prices drop 18 % yearly. Employing a cluster analysis on technology and incentive-related variables, Novizayanti et al. (2021) categorised people into four agent types (innovators, early majority, late majority, and the uncategorised one). Based on preferences, agents competed to select one of the following transportation modes: battery EV, plug-in hybrid EV and fossil fuel vehicle. According to real-world market data of conventional and electric vehicles, firms, consumers as well as some assumed values, Sun et al. (2019) developed a heuristic ABM. They shaped the model based on consumers' purchase decisions and manufacturers' performance. Moreover, Silvia and Krause (2016) used the eight following elements in their ABM to form the conceptual and decision process of the model: current age of the owned vehicle, battery EV payment, battery EV range, accessibility to alternative modes for long trips, fuel cost, environmental attitudes, innovativeness of the agent, and familiarity with the technology.

3.2.7. *Decision-making process of agents*

The decision-making process of agents about different outcomes of the model such as diffusion of EVs or modal shift to sustainable mobility options, is one of the key factors in forming conceptual frameworks of ABMs. Decision-making refers to the way in which agents make choices related to transport in each iteration of the simulation. As illustrated in Fig. 4, both theory-driven and heuristic conceptual models have used some concepts or assumptions determining how agents decide about

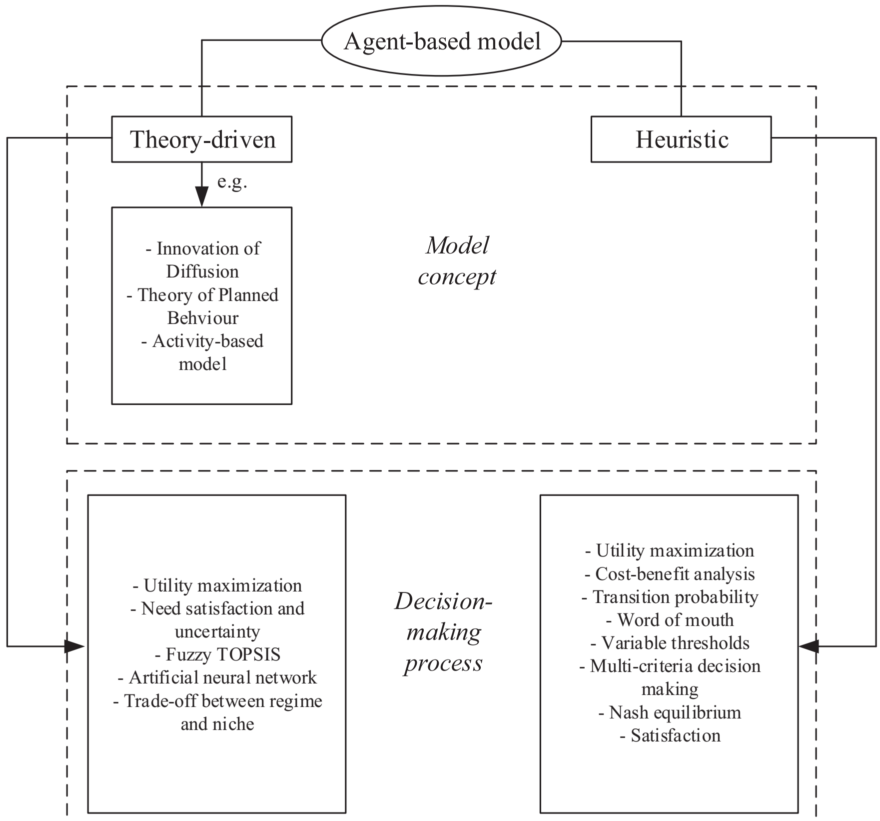

Fig. 4. Conceptual modelling framework of ABMs employed in mobility transition studies.

their choices.

Scrutinising the literature, it is evident that most choice processes in the models can be categorised in three groups: (i) rational behaviour employing random utility maximization concept (widely used by transport engineers and economists), (ii) beyond rational choice behaviour through the lens of psychological and social models, and (iii) other simple assumptions/methods such as "word of mouth", variables' thresholds, optimisation models, multi-criteria decision-making methods, cost-benefit analysis, transition probability, artificial neural network, and social network analysis.

As for random utility maximization concept, it is assumed that consumers choose an option with the maximum benefits and the minimum costs (McFadden, 1973). In other words, consumers exclude factors such as social influence and preferences in their decisions, implying that they exclusively focus on rational behaviour. Forty-four studies (51 %) exclusively used random utility maximization concept to form the decision-making process of the agents (e.g., Adepetu et al., 2016; Buchmann et al., 2021; Gnann et al., 2018; Hörl et al., 2019; Martinez and Viegas, 2017; Oh et al., 2020; Zhuge et al., 2021).

On the other hand, psychological models capture cognitive aspects of decisions, considering contextual and social influences. One of the frequently used decision-making processes, the "consumat" approach (Jager, 2000) (a combination of different psychological theories), assumes that agents conduct behaviour in a shared environment. Two key elements of mental state (i.e., needs and abilities) determine the decision strategy. According to the level of satisfaction and the uncertainty, consumer agents encounter four different information seeking (decision) strategies in each loop of the simulation: (i) Repetition (=repeating previous decisions) if they are satisfied and certain about their current behaviour, (ii) Imitation (=imitating decisions of other agents) if they are satisfied but uncertain, (iii) Optimising (=actively seeking for information) if they are unsatisfied but certain, (iv) Inquiring (=probing information from other agents) if they are unsatisfied and uncertain (Jager, 2000). A total of 10 studies (12 %) exclusively used the consumat approach for the decision-making process of the model (e.g., Faboya et al., 2020; Kangur et al., 2017; Lee and Brown, 2021b; Maggi and Vallino, 2021; Natalini and Bravo, 2013).

3.2.8. *Parametrisation or calibration method*

As for implementing an agent-based model, the following steps are generally recommended: parameterisation, calibration, and validation (Boero and Squazzoni, 2005; Sopha et al., 2017). Parameterisation refers to "*the process of selecting values for model parameters*" (Sopha et al., 2017, p. 154). Models have usually been parametrised via empirical evidence, behavioural theories and some common-sense assumptions. Calibration refers to "*selecting values of the specified model parameters to reproduce patterns observed in the real world*" (Sopha et al., 2017, p. 150). As for calibration, studies have used different data including survey data, census data, national travel surveys, real-world market data, macro data of vehicle sales, and GIS. The rest of the studies have assumed values for parameters based on some expert workshops, existing literature, and probabilistic distributions. Around 41 studies (48 %) employed survey data either exclusively or along with other data sources (e.g., census, market data) for calibration purposes.

3.2.9. *Validation*

To evaluate the extent to which an ABM can represent a real-world system, many studies try to validate their models. In general, an ABM can be validated by different approaches including requirement validation, data validation, face validation, process validation, model output validation, agent validation, and theory validation (North and Macal, 2007). As depicted in Table 2, requirement validation examines how a model responds to clear questions and requirements about the real system. Data validation refers to the fact that the valid data should be used in the model. Face validation looks at the assumptions upon the model and examines the extent to which such assumptions are plausible,

Table 2
A summary of validation perspectives.

Validation perspective	What the validation looks for?	Number of studies[a]
Requirements	What problem is the model trying to solve? Is the problem more or less important now?	0
Data	Does the model use valid data?	6
Face	Is the model based on plausible assumptions? Do the model results seem reasonable?	10
Process	Do the model's steps and internal flows match the real-world processes?	7
Model output	Does the model output match the output of the real-world system if the real-world system is available for study?	39
Agent	In the real world, do agents behave and interact the same way?	1
Theory	What theory is included in the model? Is it valid? Has the model used the theory properly?	4

[a] The number of studies applying the validation perspective.

and the model results look right. Process validation inspects how the internal flows and the steps in the model correspond to the real-world process. Model output validation, which is the most practical model validation, checks to what extent the model outputs match the outputs of the real-world system. To investigate how agent behaviours, relationships and interactions correspond to agents in the real world, agent validation is required. The last, but not the least, is theory validation. In this validation, we can validate to what extent the theory behind the conceptual framework of the model and decision-making process is valid and how the model makes a valid application of the theory.

Surprisingly, 44 studies (51 %) skipped to validate their model, of which five papers explicitly mentioned that they could not validate their model due to the lack of independent data from different sources. The remaining 39 papers did not include model validation. As for the remaining half of the studies which reported validation, most of them have only focused on model output validation using independent data from different sources. To avoid a self-evident model, validation data were not similar to that used for the calibration purposes. Among studies that reported a model output validation, research that used survey data for calibration mostly implemented their validation via macro-level data. Studies that were calibrated through macro data were validated through a macro dataset collected a year/years before the base year of the study.

3.2.10. Time horizon

We also reviewed studies to reveal what their scenario development (or simulation) approach is in terms of time horizon. The scenarios can be classified into two-time horizons: the base year scenarios and future scenarios. Future scenarios model mobility transition for upcoming years while the base year ones only recreate the base year situation. As indicated in Table B (Appendix B), a total of 53 studies (62 %) have modelled future scenarios.

3.2.11. Interaction topology (social networks)

A topology of social interactions between agents needs to be defined in order to model micro- and meso-level social influence. In the social network in which interactions take place, agents, and the links between them make up a graph representing consumer interactions. Since the adoption of innovations often involves many prospective adopters, researchers often build hypothetical networks that mimic the characteristics of real networks. Interaction (network) topology describes how different nodes (agents) in a network are connected and how they communicate with each other. In general, there are many types of social networks. Among the most common are random, small-world, cellular automata lattice, and scale-free networks (see Bohlmann et al., 2010; Kiesling et al., 2012 for a detail review).

Some models assume a complete graph or a regular structure. This type of network structure is also called cellular automata. On the other hand, other models use generative algorithms to create graphs that mimic real-life social networks. Erdos and Rényi (1960) proposed a random network topology in 1959 which represented complicated and large networks in which each node was randomly connected to some number of neighbours. Typically, the diameter of the resulting random graphs is small, i.e., the largest number of links on one of the shortest paths between any two nodes is small; this is a characteristic shared by most real-world social networks. But, in reality, social networks tend to be highly clustered, which means the probability of nodes being connected is not independent, but triadic closure is likely. In more precise terms, there is a higher conditional probability that an arbitrary pair of nodes is linked, provided both are linked to a third node (Kiesling et al., 2012). Small-world networks are networks with a small diameter and a high cluster density. The models examined in this review frequently use small-world graph models because of their topological similarities with real-world social networks. Last but not least, one notable characteristic of many social networks is the relatively high number of nodes with a degree that greatly exceeds the average (the degree refers to a node's number of links). As a result, some people serve as “hubs” within a network, due to the large number of acquaintances they have. A number of social networks (but not all) are characterized by the scale-freeness property, that is, the probability P(k) that any node in a network is connected to any number of other nodes decays as a power law. Initially, there are a few nodes linked to each other; nodes are added one by one and attached to existing nodes with probabilities based on their degrees. Therefore, the more connected a node is, the greater its chances of receiving new links. They typically are not highly clustered but are scale-free. This algorithm is also used in a few of the reviewed studies.

Although most studies in other diffusion fields, such as marketing, explicitly state which interaction topology or social network they are using in their ABMs, several resources (56 studies) in this review paper have not explicitly mentioned which social networks they have used. Research should also be conducted on how social networks influence mobility transition, as they play a vital role in the process. There is still a question of which generative algorithms and parameters are suitable for modelling interaction topologies in the mobility transition.

3.2.12. Key findings of studies

Key findings of studies have been summarised in Appendix D. Although a study reported that preference-based policies are more effective than price-based ones on the diffusion of sustainable modes (Maggi and Vallino, 2021), many other studies highlighted the strong power of price-based scenarios (Adepetu and Keshav, 2017; Bühne et al., 2015; Choi, 2016; Schröder and Wolf, 2017). A study also recommended a combination of preference and price-based policies (Natalini and Bravo, 2013). As for the target agents of subsidy policies, the findings are consistent. For example, Sun et al. (2019) concluded that consumer subsidies are more effective than manufacturer subsidies on EVs diffusion. Moreover, Noori and Tatari (2016) showed that consumer subsidies have the most impact on EVs diffusion. Many reported that a decrease in battery costs results in increased uptake of Plug-in Hybrid EVs (PHEVs) (Eppstein et al., 2011; Kangur, 2014; Kangur et al., 2017; Zhuge et al., 2021). Regarding the role of shared automated vehicles, most studies showed a positive impact on future mobility and environment in terms of emissions (Fagnant and Kockelman, 2014; Hörl et al., 2019; Martinez and Viegas, 2017), while one study concluded that such emerging mobility may be a threat for public transit services (Liu et al., 2017). In addition, two studies recommended that Automated Mobility on-Demand (AMoD) should be used along with mass transit (Basu et al., 2018; Oke et al., 2020). AMoD is a mobility as a service which allows people to take an automated vehicle at any time and location. Other studies also highlighted that technological progress in different aspects of EVs (e.g., charging time, range, and station) can noticeably promote PHEV market shares (Geerlings, 2020; Klein et al., 2020; Silvia and

Krause, 2016; Vooren and Alkemade, 2012; Zhang et al., 2011).

4. Analysis of main results and positioning map

Taking a closer look at the study results indicates that the current state-of-the-art can be divided into different clusters. By clustering the studies, we sort them conceptually into meaningful groups. Mobility transition studies employing ABM can be conceptually categorised into eight groups based on pivotal technical aspects of studies and ABM approaches (e.g., aims of the study or kind of mobility transition, conceptual framework of the model, and decisions making process of agents). A conceptual clustering like this would be a good starting point for further research into agent-based modelling of mobility transition. Future studies in this area can gain insight into how to shape the study's framework and decision-making mechanism according to available data and research topics. Three aspects (variables) with the following definitions were considered in the conceptual clustering.

- The kind of transition which studies focus on: *EV transition* versus *non-EV transition* (other kinds of mobility transition studies such as modal shift, shared mobility, automated vehicles).
- The conceptual framework of the developed ABMs: *theory-driven* versus *heuristic*.
- The decision-making mechanism of agents; *utility maximization* or *other* approaches (e.g., psychological, threshold).

Eight different clusters are shown in Fig. 5. The reviewed studies with similar features/characteristics are located within the same clusters. The codes depicted in this diagram match those defined in Table B (Appendix B). For the sake of simplicity, the kind of mobility transition in the illustration is shown with two colours of blue (EV transition) and red (non-EV transition). The following eight groups can thus be distinguished.[4]

- Cluster A: studies that focus on the transition to EVs using a theory-driven framework where the decision-making processes of agents are based on utility maximization. There are 10 studies in this cluster out of 86.
- Cluster B: studies that focus on the transition to non-EVs (other kinds of transitions) using a theory-driven framework where the decision-making processes of agents are based on utility maximization. A total of 16 studies comprises cluster B.
- Cluster C: studies that focus on the transition to EVs employing a heuristic framework where the decision-making processes of agents are based on utility maximization. This cluster consists of 11 studies (accounting for S56 as well).
- Cluster D: studies that focus on the transition to non-EVs (other kinds of transitions) employing a heuristic framework where the decision-making processes of agents are based on utility maximization. A total of 10 studies (accounting for S56 as well) are included in this cluster.
- Cluster E; studies that investigate the transition to non-EVs (other kinds of transitions) using a theory-driven framework where the decision-making processes of agents are based on other approaches (e.g., thresholds, psychological). A total of 10 studies comprises this cluster.
- Cluster F; studies that investigate the transition to EVs using a theory-driven framework where the decision-making processes of agents are based on other approaches (e.g., thresholds, psychological). A total of eight studies have been included in this cluster.
- Cluster G; studies that investigate the transition to non-EVs (other kinds of transitions) using a heuristic framework where the decision-making processes of agents are based on other approaches (e.g., thresholds, psychological). This cluster contains 11 studies (including S13 and S16 as well).
- Cluster H; studies that investigate the transition to EVs using a heuristic framework where the decision-making processes of agents are based on other approaches (e.g., thresholds, psychological). This cluster contains 15 studies (including S13 and S16 as well).

From the analysis, first, it is evident that most studies, except S13, S16, and S56, only addressed one kind of mobility transition through ABM. Approximately half of the studies focused on EV transition, and the rest on other mobility transitions (e.g., shared services, automated vehicles). Future ABMs are necessary to consider different kinds of mobility transitions simultaneously. Second, when it comes to the conceptual framework of the model and decision-making process of agents, studies can be categorised into four distinguishable groups. One set of studies has developed a theoretical framework (e.g., psychological models and activity-based models) where agents choose mobility options based on utility maximization. This set includes studies in clusters A and B. Another set of studies has developed a heuristic framework where agents choose mobility options based on utility maximization. Studies in clusters C and D are included in this set. A set of studies has developed a theoretical framework where agents choose mobility options based on other approaches such as psychological needs and satisfactions or some thresholds. This set contains studies in clusters E and F. Finally, a set of studies has developed a heuristic framework where agents choose mobility options based on other approaches (non-utility maximization). This set contains studies in clusters G and H.

However, in one study (S69), both decision-making processes were tested on a theory-driven ABM. According to Sopha et al. (2017), psychological decision-making processes (the "consumat" approach) of agents could explain the underlying mechanisms of natural gas vehicle adoption better than rational utility maximization. This issue could be explored further in future studies by testing and comparing both decision-making processes.

5. Concluding remarks and future research direction

We systematically reviewed the agent-based modelling/social simulation paradigm in mobility transition studies. This systematic review highlights that the field is maturing, with a wealth of well-understood methods and algorithms. However, a closer look at the literature reveals several gaps and shortcomings. According to the review, the following major remaining challenges and gaps could be identified.

First, the literature has a rich research background on EV diffusion and half of the studies simulated EV uptake as a mobility transition. Future studies could also simulate new aspects of EVs such as willingness-to-pay for EVs with Vehicle-to-Grid[5] (V2G) contracts. The V2G is a technology where EVs will be able to transfer electricity back to the power network. The battery of the car will charge when power is cheap and will return power to the network during high traffic/peak hours saving both energy and money. Meanwhile, other kinds of transitions (e.g., mobility services, automated vehicles, bike sharing) have rarely been studied directly through ABMs. Future studies could fruitfully model such transitions. Moreover, the majority of prior research has only focused on one kind of mobility transition in their simulation. Neglecting how the role of other kinds of emerging mobilities and their interactions may lead to a bias in forecasting future transport systems. We believe that apart from looking for one specific transition, future research should look for a variety of mobility transitions and potentially model the interrelations in ABMs.

Second, it remains unclear to which degree a price-based policy or a preference-based strategy can influence the diffusion of sustainable

[4] Some studies go into several clusters.

[5] Drawing unused power from the EV into the smart grid.

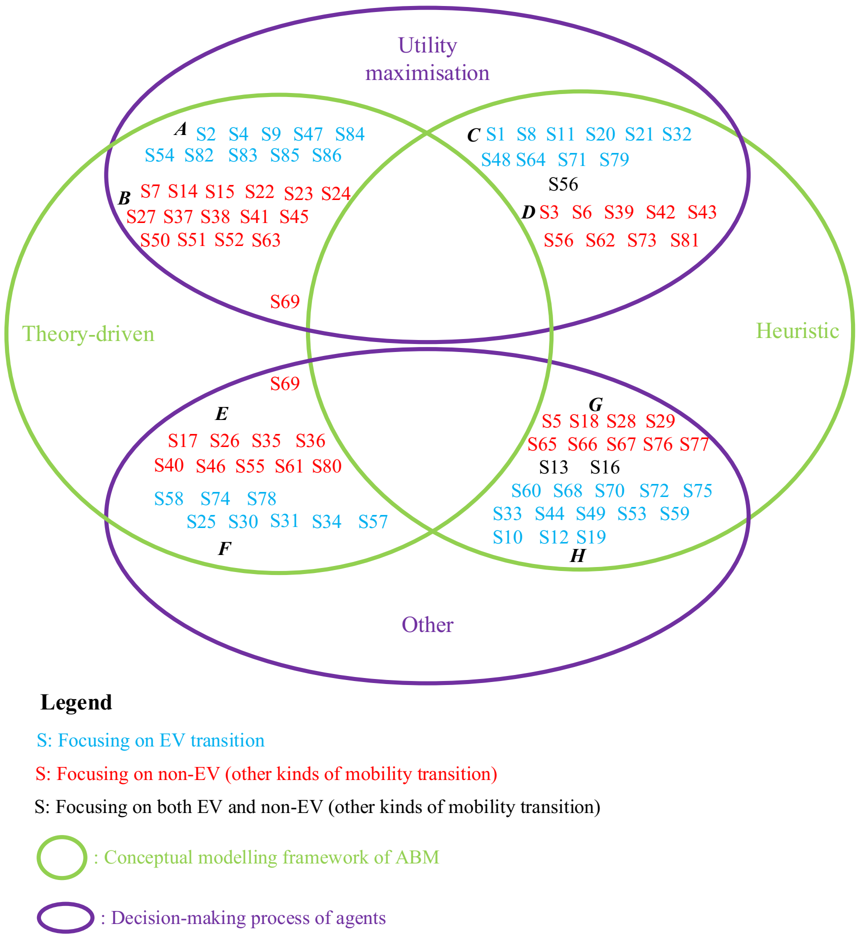

Fig. 5. A conceptual clustering of the current state of the research.

mobility options in the past simulations. Looking forward, attempts could still examine the competitive role of these policies on mobility transition studies.

Third, most of the previous research has been confined to developed countries such as the US, the Netherlands, Germany, China, Switzerland, the UK, or Italy. Future research should be conducted in other settings to understand the key components of transition in the transport system more comprehensively. From this standpoint, the state-of-the-art agent-based modelling would benefit from the same type of research in other developed regions such as Scandinavian countries (e.g., Norway), France, Canada, Australia, New Zealand, and Japan. Furthermore, the relative gain of policy development may be higher in developing countries with large populations. Future research should be extended to developing regions in Eastern Europe, Eastern Asia, Middle East, South America, and Africa with their specific mobility transition pathways. In the mobility sector, we speculate that technology (e.g., EV developments, micro-mobility) is not progressing as fast as it is in Western nations. Possibly, this explains why fewer simulations (ABMs) have been used regarding mobility transition outside of Western countries. Most studies in non-Western countries use econometric and statistical models to predict/explain base year transport modal shares. We expect that the spread of emerging mobility options will lead to greater use of ABM in non-western nations in the future.

Fourth, although the literature can take advantage of both theory-driven and heuristic agent-based models, we recommend employing a theory-driven approach. Since theory-driven models use well-established behavioural frameworks, causal links between variables and decision rules (algorithms) are more straightforward. Theory-driven models also benefit from behavioural rules which consider heterogeneous decisions of agents. Psychological frameworks, such as Roger's Diffusion of Innovation Theory, the Consumat framework, the Theory of Planned Behaviour, and non-psychological concepts such as activity-based travel models are desirable approaches for future work. As for the decision-making process, most of the algorithms have used the random utility maximization (RUM) concept, beyond rational choice behaviour through the lens of psychological and social models, and other simple assumptions/methods. We believe that apart from these behavioural rules, random regret minimisation (RRM) concept (Chorus, 2012) is also highly relevant in mobility transition studies (i.e., diffusion of more sustainable transport modes). Contrary to RUM theory, RRM concept is a non-utilitarian discrete choice model in which consumers tend to minimise regret rather than maximise utility (Chorus, 2012). When it comes to the diffusion of sustainable travel options such as EVs, people may choose a travel mode that reduces their regret in terms of environmental impacts. The HUMAT framework developed in the SMARTEES[6] project – a study on transition to energy efficiency and sustainability – has some characteristics along this concept. However, to our knowledge, such an approach has not been implemented in ABMs simulating mobility transitions.

Fifth, according to the availability of data and research questions, most ABMs have been calibrated by self-reported surveys, census data, national travel surveys, market data, macro data of vehicle sales, and GIS. Hence, we recommend using self-reported survey data for calibration of theory-driven frameworks in addition to employing rich real-

[6] Social innovation modelling approaches to realizing transition to energy efficiency and sustainability.

world market data.

Sixth, as for validation of ABMs, half of the studies did not validate their models. We believe that simulation validation should be a non-negotiable part of reporting ABMs. As asserted by North and Macal (2007), different approaches can be employed for ABM validation such as theory validation, requirement validation, process validation, agent validation, data validation, face validation, and model output validation. Future research should consider the potential validation techniques more carefully. Moreover, a total of 62 % ABMs developed future scenarios. As for simulating mobility transition, future studies should not only rely on base year scenarios.

Seventh, most studies fail to explain the topology of interaction (social networks) in their ABMs. It is recommended that future studies explicitly state how agents are linked to one another. Research is also needed to determine which social networks are appropriate for mobility transitions. There are some limitations to the current study. Since we searched for resources in August 2021, the study lacks papers published after this month. This issue may have affected our depiction of the rate of publications by year. When we conceptually categorised studies into eight clusters, we excluded some aspects of ABMs (e.g., interaction topology, calibration). The reason is that such aspects have not been specified consistently throughout most of the studies. By considering such aspects, our conceptual clustering would have been significantly improved.

CRediT authorship contribution statement

Milad Mehdizadeh: Writing - original draft; Conceptualization; Methodology; Investigation; Formal analysis; Resources; Data Curation; Visualization; Funding acquisition; Project administration.

Trond Nordfjaern: Supervision; Validation; Writing - review & editing; Project administration.

Christian A. Klöckner: Supervision; Validation; Writing - review & editing; Funding acquisition; Project administration.

Financial disclosure

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Declaration of competing interest

The authors have no conflict of interest to report.

Data availability

No data was used for the research described in the article.

Appendix A

Table A
Classification of selected references for review.

Reference classification	No.	%
Source		
Journal	77	89.53
Thesis	6	6.98
Book chapter	3	3.49
Journal division		
Transportation Research Part A: Policy and Practice	5	5.81
Energy Policy	5	5.81
Technological Forecasting and Social Change	5	5.81
Transportation Research Part C: Emerging Technologies	4	4.65
Energies	4	4.65
Journal of Cleaner Production	3	3.49
Transportation	3	3.49
International Journal of Sustainable Transportation	3	3.49
Transportation Research Record: Journal of the Transportation Research Board	3	3.49
Journal of Environmental Psychology	3	3.49
Transport Policy	2	2.33
Transportation Research Part D: Transport and Environment	2	2.33
IEEE-related publications	2	2.33
Energy	2	2.33
Journal of Artificial Societies and Social Simulation	2	2.33
Journal of Advanced Transportation	1	1.16
Sustainable Cities and Society	1	1.16
Resources, Conservation and Recycling	1	1.16
World Electric Vehicle Journal	1	1.16

(continued on next page)

Table A (*continued*)

Reference classification	No.	%
Research in Transportation Business & Management	1	1.16
Sustainable Production and Consumption	1	1.16
Computers & Industrial Engineering	1	1.16
Applied Energy	1	1.16
Case Studies on Transport Policy	1	1.16
International Journal of Transportation Science and Technology	1	1.16
Preventive Medicine	1	1.16
Future Generation Computer Systems	1	1.16
Science, Technology and Society	1	1.16
Journal of Infrastructure Systems	1	1.16
Journal of Development Effectiveness	1	1.16
Environmental Science & Technology	1	1.16
Transport Reviews	1	1.16
Sustainability	1	1.16
Journal of Product Innovation Management	1	1.16
Ecological Economics	1	1.16
iScience	1	1.16
Energy Reports	1	1.16
Journal of Computational Science	1	1.16
Research in Transportation Economics	1	1.16
European Transport Research Review	1	1.16
Energy Research & Social Science	1	1.16
Transportation Science	1	1.16
Communications in Nonlinear Science and Numerical Simulation	1	1.16
Journal of Evolutionary Economics	1	1.16

Appendix B

Table B
A summary of reviewed papers.

No.	Study	Aim	Variables embedded in the model	Policy scenario[a]	Region	Target agent or population	Conceptual modelling framework[b]	Decision-making process[c]	Parametrisation or calibration	Validation	Time horizon	Interaction topology
S1	Adepetu and Keshav, 2017	Exploring the effect of a high-capacity battery and EV rebates on an EV ecosystem	Demographic, socioeconomic	Four scenarios about high-capacity battery and EV rebates	Los Angeles, California, the US	Individuals	Heuristic, EV adoption model	Utility maximization	A survey conducted by the National Renewable Energy Laboratory's (NREL's) secure transportation data project	Not specified	Future. From 2014 to 2018	Random, small-world
S2	Adepetu et al., 2016	Exploring EV adoption	Demographic, socioeconomic, vehicle attributes, EV ecosystem, charging options	Base scenario, No rebates for EVs, An additional rebate of $ 2000 for all EVs	San Francisco, the US	Individuals	Theory-driven, ecosystem model	Utility maximization	A survey conducted by the National Renewable Energy Laboratory's (NREL's) secure transportation data, different real data	Not specified	Future. From 2014 to 2018	Random, small-world
S3	Ahanchian et al., 2019	Exploring modal shift behaviour	Travel attributes, demographic, socioeconomic	Business as usual (BAU), Expansion of public infrastructure, Incentives for sustainable modes, Disincentives for private cars, Combination of all scenarios	Denmark	Travellers	Heuristic	Utility maximization	TU survey database, travel demand from 2010 until 2015	Historical modal share in 2015. Model output Validation	Future. from 2010 to 2050	No interaction
S4	Ahkamiraad and Wang, 2018	Exploring EV adoption + electricity consumption	Land use, Socioeconomic	Three scenarios based on the different market share of car fleet	New York, the US	175 zip codes	Theory-driven, the Fisher and Pry diffusion model and Rogers model	Utility maximization	The Official Website of New York State, United States Zip Codes	Not specified	Future. from 2015 to 2050	Not specified
S5	Arian and Chiu, 2017	Evaluating the promotion of emerging mobility options	Travel attributes	Different patterns of social network	Austin, Texas, the US	Individuals	Heuristic, a hazard-based duration model	A social network algorithm	Empirical data from an Austin, Texas-based innovative mobility solution, the Metropia app	Not specified	Future. 160-time steps	Fully-connected network
S6	Aziz et al., 2018	Investigating the effects of infrastructure investment decisions on active mode use	Travel attributes, built-environment	Improving walk-bike infrastructures, wide sidewalks and longer bike lanes, Reducing pedestrian and bike crashes	New York, the US	Workers	Heuristic	Utility maximization	Generated from extended penalized maximum entropy dasymetric model	Without validation	Base year	Not specified
S7	Basu et al., 2018	Exploring the impact of AMoD on urban mobility	Travel demand and supply	A base case, without mass transit, with AMoD	A virtual city	Travellers	Theory-driven, activity-based framework, SimMobility	Utility maximization	Generated data	Not specified	Base year	Not specified
S8	Brown, 2013	Exploring EV adoption	Demographic, socioeconomic, vehicle attributes, battery attributes, fuel prices	Price, government financial incentives, battery cost, fuel cost,	Boston, the US	Individuals	Heuristic	Utility maximization	The US Department of Transportation's 2009 National Household Travel Survey	Not specified	Future. From 2009 to 2030	Not specified

(*continued on next page*)

Table B (*continued*)

No.	Study	Aim	Variables embedded in the model	Policy scenario[a]	Region	Target agent or population	Conceptual modelling framework[b]	Decision-making process[c]	Parametrisation or calibration	Validation	Time horizon	Interaction topology
S9	Buchmann et al., 2021	Exploring EV adoption	Demographic, socioeconomic (individuals and households), vehicle attributes	Three governmental measures	Germany	Household, vehicle	Theory-driven, Roger's diffusion model	Utility maximization	The history-friendly calibration, diffusion of PHEV and BEV within the period 2007 to 2018.	Expert validation. Process and agent validations	Future. 2020 to 2030	Geographical closeness of word of-mouth
S10	Bühne et al., 2015	Exploring EV adoption	Demographic, socioeconomic, attitudes	Different electromobility scenarios	Europe	Individuals	Heuristic	Not specified	European wide online consumer survey.	Not specified	Future. From 2015 until 2030	Not specified
S11	Chaoxing, 2017	Exploring EV adoption	Resident, dealer, manufacturer and vehicle attributes	The base, purchase price, disposition towards EVs in early years, Change EV drive train cost, Change car ownership period	the Netherlands	Consumers, a car manufacturer, a car dealer and cars	Heuristic	Utility maximization	A large amount of real market data	Not specified	Future. From 2016 to 2035	Not specified
S12	Chaudhari et al., 2019	Exploring EV charging load adoption	Micro and macro-level variables	Different demand-supply scenarios related to EVs	Singapore	EVs	Heuristic	Optimization based on agent's objectives	Aggregated data	Not specified	Future, 24 h	Not specified
S13	Choi, 2016	Exploring EV and hybrid vehicle adoption	Vehicle and government attributes	Vehicle prices, subsidies/penalties and tax incentives	Korea	Consumers, manufacturers, fuel suppliers and government	Heuristic	Cost-benefit	Available real aggregated data	Not specified	Base year	Not specified
S14	Ciari et al., 2016	Exploring carsharing adoption	Demographic, socioeconomic, vehicle attributes	Several scenarios with different levels of carsharing supply (both stations based and free-floating)	Zurich, Switzerland	Individual	Theory-driven, activity-based microscopic transport modelling, MATSim	Utility maximization	Census data, the customer data from the city of Munich (DriveNow)	Comparing with actual data. Model output validation	Base year	Not specified
S15	de Haan et al., 2009	Exploring hybrid vehicle adoption	Market statistics, vehicle attributes, fuels	Incentives for very fuel-efficient cars to paying additional fees for highly inefficient cars	Switzerland	Households	Theory-driven, Prospect theory and choice theory	Utility maximization	A mail-back survey among Swiss households, Swiss data, model output	Comparing with 2005 Swiss market data. Model output validation	Base year	Not specified
S16	Eppstein et al., 2011	Exploring PHEV adoption	Demographic, socioeconomic, vehicle attributes, travel attributes, fuel, built-environment	Fuel costs, PHEV purchase price and rebates, to PHEV Battery range, gasoline usage	Hypothetical city, the US	Potential new-car buyers	Heuristic	Cost-benefit	Assumed values and generated data, existing literature	Not specified	Base year	Random, homophily and conformity
S17	Faboya et al., 2020	Exploring modal shift behaviour	Transport needs (e.g., safety, convenience)	Travellers' average daily satisfaction, Travellers' mode shift diffusion pattern, Travellers' cognitive processing, a combined one	UK	Travellers	Theory-driven	Psychological model (Jager, 2000).	A survey; 348 participants through questionnaires	Process, face, data, and model output validation	Future. 365 days	Not specified
S18	Fagnant and Kockelman, 2014	Exploring travel and environmental implications of shared autonomous vehicles	Travel attributes	Trip generation scenarios, Demand-centralization, Service-area, return-trip by SAV, less-congested-peak, more-congested peak, SAV demand	Austin, Texas, the US	Travellers	Heuristic	Heuristic	2009 NHTS data	Not specified	Base year	Not specified

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No.	Study	Aim	Variables embedded in the model	Policy scenario[a]	Region	Target agent or population	Conceptual modelling framework[b]	Decision-making process[c]	Parametrisation or calibration	Validation	Time horizon	Interaction topology
S19	Geerlings, 2020	Exploring EV adoption (spatial and dynamic perspectives)	EV attributes (e.g., battery capacity, range, speed), charging attributes (location, energy rate, sockets)	Policies and technologies.	Amsterdam, the Netherlands	The EV agents, the charging point agents	Heuristic	Satisfactions	Real-life spatial and EV datasets	Comparing with actual data. Face and model output validation	Base year	Not specified
S20	Gnann et al., 2015	Exploring EV adoption	Vehicle attributes, charging attributes, cost	Pro-EV scenario, medium scenario, contra-EV scenario	Germany	Users of private vehicles, fleet vehicles, and company cars	Heuristic	Utility maximization	Different sources such as the German Mobility Panel, two data sets for the willingness to pay more (WTPM) for EVs	Not specified	Future. From 2011 to 2020	Not specified
S21	Gnann et al., 2018	Exploring EV adoption (the role of public slow charging)	Driving profiles, favouring and limiting factors	No subsidy, subsidy until 2020, subsidy until 2030	Germany	Individual vehicles	Heuristic, Alternative Automobiles Diffusion and Infrastructure (ALADIN)	Utility maximization	7-day mobility survey with about 5000 households, 21 days on average with GPS trackers for fleet vehicles	Not specified	Future. From 2015 to 2030	Not specified
S22	Hajinasab et al., 2016	Exploring modal shift behaviour	Demographic, socioeconomic, contextual factor	Reducing the public transport fare, doubling the public transport fare	Malmö-Lund, Sweden	Passengers	Theory-driven, ASIMUT. Discrete choice model	Utility maximization	Web services provided by online travel planners	Not specified	Base year	Not specified
S23	Hörl et al., 2019	Exploring the impact of AMoD on urban mobility	Travel demand and supply	Four different operational policies	Zurich, Switzerland	Travellers	Theory-driven, MATSim	Utility maximization	National household travel survey, different Swiss data sets	Not specified	Base year	Not specified
S24	Hörl et al., 2021	Exploring the impact of AMoD on urban mobility	Demand patterns, cost	Price, customer behaviour and system impact	Zurich, Switzerland	Travellers, vehicle	Theory-driven, MATSim	Utility maximization	National household travel survey, different Swiss data sets	Not specified	Base year	Not specified
S25	Huang et al., 2021	Exploring EV adoption	EV attributes, travel attributes, vehicle attributes, cost, price, charging attributes, innovativeness, environmental attitudes	Government subsidy, public charger, hybrid policy	Chongqing, China	Governments, automakers and consumers	Theory-driven	Fuzzy TOPSIS method	China's auto market for 2019 and 2020, survey results from existing literature, questionnaires, realistic assumptions	Not specified	Future. 20 years	Small-world
S26	Huétink et al., 2010	Exploring hydrogen vehicles adoption	Fuel station, adopter rates, learning ability	Very high policy support and fast learning, high policy support and fast learning, High policy support, modest learning, Modest policy support, modest learning	Hypothetical region, the Netherlands	Consumers and refuelling stations	Theory-driven, the diffusion of innovations, the model of Rogers	The trade-off between consumers and refuelling stations	Assumed values	Not specified	Future. From 2010 to 2200	Small-world, random
S27	Hussain et al., 2016	Exploring carpooling adoption	Travel demand and supply	Carpooling	Flanders, Belgium	Carpooling agent, non-carpooling agent	Theory-driven, activity-based model and organisational model	Utility maximization	FEATHERS for the Flanders region	Not specified	Future. 146 days	Random

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No.	Study	Aim	Variables embedded in the model	Policy scenario[a]	Region	Target agent or population	Conceptual modelling framework[b]	Decision-making process[c]	Parametrisation or calibration	Validation	Time horizon	Interaction topology
S28	Inturri et al., 2021	Comparing innovative Demand Responsive Shared Transport (DRST) with taxies	Numbers of vehicles, seat capacity, demand, route choice strategies	Different values of variables for both taxi and DRST	Ragusa, Italy	Passenger and vehicle dynamic	Heuristic	Variables' threshold	A GIS dataset at the census tracts scale	Not specified	Base year	Not specified
S29	Inturri et al., 2019	Planning and designing new shared mobility services	Service variables, demand, route choice strategy	System operation with different numbers of vehicles, different route choice strategies with increasing levels of randomness	Ragusa, Italy	Passenger and vehicle	Heuristic	Variables' threshold	A GIS dataset at the census tracts scale	Not specified	Base year	Not specified
S30	Kangur et al., 2017	Exploring EV adoption	Demographic, socioeconomic, vehicle attributes, travel attributes, preferences	New cars entering the market, Purchase power, Service stations and prices, Taxation	the Netherlands	Individuals	Theory-driven, the STECCAR model	Psychological model, needs and satisfaction	A survey from 1795 respondents, empirical supports and the literature.	Data from July 2012 until July 2014. Model output validation	Future. from 2012 to 2025	Small-world, random
S31	Kangur, 2014	Exploring EV adoption	Demographic, socioeconomic, vehicle attributes, travel attributes, preferences	Policy scenarios: The government takes charge, Development scenarios: Technology powers up, combination scenarios	Dutch citizen, the Netherlands	Individuals	Theory-driven, Psychological model, Consumat framework	Psychological model (Information seeking strategies, satisfaction and uncertainty)	Dutch online questionnaire from June 2012	Comparing with actual data. Model output validation	Future. From 2012 to 2025	Small-world, random
S32	Kieckhäfer et al., 2014	Exploring EV adoption	Vehicle attributes	Analysing market share based on different group membership	Germany	Vehicles	Heuristic, integration of system dynamics and ABM	Utility maximization	Real-world data	Face, process, data, and model output validation	Future. From 2009 to 2029	Not specified
S33	Kieckhäfer et al., 2017	Exploring EV adoption (manufacturers' impact)	Purchase decision, manufacturer, technology development, infrastructure	Pessimistic, Realistic, Optimistic	Germany	New car buyers, which leads to 18,834 agents	Heuristic, AMaSi model, an integration of system dynamics and ABM	Transition probabilities	German car market	Comparing with actual data. Face, process, data, and model output validation	Future. from 2010 to 2030	Small-world
S34	Klein et al., 2020	Exploring EV adoption (purchasing decision)	Engine type, Price, consumption costs, station density, station charging time (EV only), Range (EV only), home charging possibility (EV and PHEV only)	technological progress, a subsidy scenario, a fast-charging scenario, home charging scenarios	Germany	Vehicles, consumers, producers	Theory-driven	Psychological model (grounded on Rogers' (2003) five stages of adoption)	Choice-based data ($n = 552$) and additional data regarding home charging facilities	Face, process, data, model output, and theory validation	Future. a 15-year time horizon	Small-world
S35	Köhler et al., 2009	Exploring alternative fuel vehicle adoption	Travel attributes, costs, emission rates, built-environment	a scenario storyline of a possible transition pathway	The UK	Simple (consumers) agents, complex (regime and niches) agents	Theory-driven, transition theory	A trade-off between regime and niche	Real-world data, UK transport data	Not specified	Future. From 2000 to 2050	Not specified
S36	Köhler et al., 2020	Exploring modal shift behaviour	Vehicle attributes, travel attributes.	A technological substitution pathway, a reconfiguration	the Netherlands	Consumers, regime, niche	Theory-driven, MATISSE based on socio-technical	A trade-off between regime and niche	A series of expert workshops, Empirical data for the	Comparing with the MATISSE model. Model	Future. from 2015 to 2050	Not specified

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No.	Study	Aim	Variables embedded in the model	Policy scenario[a]	Region	Target agent or population	Conceptual modelling framework[b]	Decision-making process[c]	Parametrisation or calibration	Validation	Time horizon	Interaction topology
		(low carbon mobility)		pathway on personal ownership of a car.			transitions analysis and qualitative system modelling		Netherlands were taken from CBS (2015)	output validation		
S37	Lemoine et al., 2016	Exploring the effect of Bus Rapid Transit (BRT) system on walking	Home and work location, socioeconomic	Development of Bus Rapid Transit (BRT)	Bogotá, Colombia	Individuals	Theory-driven, Activity-based travel demand model	Utility maximization	Bogota's 2011 mobility survey	Comparing with actual data. Model output validation	Future (short term), 30 days	Not specified
S38	Liu et al., 2017	Exploring shared autonomous vehicles adoption	Travel demand and supply	Four fare rates with fixed costs	Austin, Texas, the US	Travellers and vehicles	Theory-driven, activity-based model, MATSim	Utility maximization	Extensive travel demand data at the level of individual travellers	Not specified	Base year	Not specified
S39	Lu et al., 2018	Exploring bike-sharing adoption	Travel time, cost, accessibility, ownership status	Bike infrastructure extensions, bike-sharing incentives	Taipei, Taiwan	Passengers and transport modes	Heuristic	Utility maximization	Travel survey collected from 2009 to 2015,	Comparing with previous research. Model output validation	Base year	Not specified
S40	Maggi and Vallino, 2021	Exploring modal shift behaviour	Cost, emissions rates, preferences	Price versus preference-based	Varese, Italy	Individuals	Theory-driven	Psychological model, (Information seeking strategies, satisfaction and uncertainty)	Data from the Italian National Statistical Institute	Face, and model output validation	Base year	Not specified
S41	Martinez and Viegas, 2017	Exploring ridesharing and self-driving fleet adoption	Demographic, socioeconomic, land use, car and public transport monthly pass availability, transport operation attributes	Three main scenarios, current car, taxi and bus trips were replaced for shared mobility alternatives	Lisbon, Portugal	Users, vehicles, and dispatcher	Theory-driven, activity-based model	Utility maximization	Travel survey	Not specified	Base year	Social circle (large-world)
S42	Martinez et al., 2015	Exploring shared-taxi system adoption	Sociodemographic variables, travel-related attributes,	With the current taxi fleet, with shared taxis	Lisbon, Portugal	Client agent, Taxi agent,	Heuristic,	Utility maximization	Mobility survey	Comparing with actual data. Model output validation	Base year	Not specified
S43	Martínez et al., 2016	Exploring carsharing adoption	Socio-demographic attributes, land use, car and public transport availability, transport operation attributes	Reservation, relocation	Lisbon, Portugal	Users and the carsharing operator, vehicles and staff.	Heuristic, optimisation model	Utility maximization	Mobility survey	A rough validation by census data. Model output validation	Base year	Not specified
S44	McCoy and Lyons, 2014	Exploring EV adoption	Socioeconomic	Base scenario	Ireland	Households	Heuristic	Adoption status	Detailed survey microdata, Irish Census 2011 data	Not specified	Future. 15-time steps	Random, small-world and scale-free
S45	Mueller and de Haan, 2009	Exploring modal shift behaviour (impact of policy leavers)	Demographic, socioeconomic	Without scenarios	Switzerland	Individuals	Theory-driven, Prospect theory and choice theory	Utility maximization	Swiss data	Market observations. Model output validation	Base year	Not specified
S46	Natalini and Bravo, 2013	Exploring modal shift behaviour	Demographic, socioeconomic, preferences, travel attributes	Market-based policies, preference-change policies, interactions among policies	the USA	American commuters	Theory-driven, Consumat framework	Psychological model (Informationseeking strategies, satisfaction and uncertainty)	A subsample from the 2009 NHTS survey	Model output validation	Base year	Small-world
S47	Ning et al., 2019	Exploring EV adoption	Socioeconomic (worker and student groups)	Without scenario development	Jiading, Shanghai, China	Workers and students	Theory-driven, the diffusion model under social network environment	Utility maximization	Surveys	Not specified	Future, The time step is not specified.	Small-world, graph

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No.	Study	Aim	Variables embedded in the model	Policy scenario[a]	Region	Target agent or population	Conceptual modelling framework[b]	Decision-making process[c]	Parametrisation or calibration	Validation	Time horizon	Interaction topology
S48	Noori and Tatari, 2016	Exploring EV adoption	Random variables (distribution functions)	Government subsidies scenario, word-of-mouth	The US	Consumers, regions, governments, and vehicles	Heuristic, Exploratory Modelling and Analysis, (EMA) method	Utility maximization	The 2009 NHTS (National Household Travel Survey), U.S. census data and the Population Explorer tool	Face, model output, and theory validation	Future. From 2015 to 2030	Not specified
S49	Novizayanti et al., 2021	Exploring EV adoption	EV attributes, monetary incentive	Incentives and technology-related changes	Indonesia	General population. Innovators, early majority, late majority, and the uncategorised one	Heuristic, the Twitter data was retrieved from its Application Program-ming Interface (API)	Not specified	A survey; 161 online questionnaire data	Not specified	Future. 2020 to 2040	Not specified
S50	Novosel et al., 2015	Exploring alternative fuel vehicle adoption and modal shift behaviour (energy demand modelling)	Demographic, socioeconomic, energy attributes	Different energy-related scenarios	Croatia	Travellers	Theory-driven, MATSim, EnergyPLAN	Utility maximization	Aggregated socio-demographic input data for Croatia's four biggest cities, Meteorological data	Comparing with data listed on the IEA website. Model output validation	Base year	Not specified
S51	Oh et al., 2020	Exploring the impact of AMoD on urban mobility	Travel demand and supply	Pricing, Fleet sizing, Performance measures	Singapore	Travellers	Theory-driven, activity-based model system, SimMobility	Utility maximization	A smartphone-based stated preferences survey, 350 respondents and 2500 SP observations	Pre-day model for the year 2012. Model output validation	Future, for the year 2030	Not specified
S52	Oke et al., 2020	Exploring the impact of AMoD on urban mobility	Demographic, socioeconomic, built-environment	Base case, AMoD Intro, AMoD No Transit, AMoD Transit Integration	World's cities, by classifying 12 urban typologies	Two prototype cities	Theory-driven, SimMobility MidTerm PreDay activity-based model structure	Utility maximization	Data were gathered from 331 metropolitan areas worldwide	Using the control Variables. Model output validation	Base year	Not specified
S53	Olivella-Rosell et al., 2015	Estimating EV charging demand	EV attributes, GDP, population, density, travel attributes	Different charging scenarios	Barcelona, Spain	EV agents	Heuristic, charging demand algorithm based on Monte Carlo	Trade-off between variables	Automaker's data	Without validation	Base year	Not specified
S54	Pagani et al., 2019	Estimating user behaviour and EV charging infrastructure	EV attributes, source of revenues, charging attributes, preferences	Revenues, charging behaviour of, preferences and new EV charging infrastructure	Switzerland	The entire Swiss driving population of 5,200,000 agents	Theory-driven, EnerPol, activity-based demand model	Utility maximization	Detailed databases of different Swiss Federals	Comparing with actual data. Model output validation	Base year	Not specified
S55	Querini and Benetto, 2015	Exploring modal shift behaviour	EV attributes, demographic, socioeconomic	No EVs, different charging scenarios at workplaces	Luxembourg	Individuals	Theory-driven, Life cycle assessment	Variables' threshold	The ecoinvent database, real data of market share	Without validation	Future. From 2013 to 2020	Not specified
S56	Querini and Benetto, 2014	Exploring EV and hybrid vehicle adoption	Demographic, socioeconomic	Default, Electric-Vehicle Oriented (EVO) and Economy Constrained (ECO)	Luxembourg and Lorraine	Individuals aged above 18 are considered, households	Heuristic	Utility maximization	Luxembourgish and the French national statistics, car sale data	Comparing with actual data. Model output validation	Future. From 2013 to 2020	Random

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No.	Study	Aim	Variables embedded in the model	Policy scenario[a]	Region	Target agent or population	Conceptual modelling framework[b]	Decision-making process[c]	Parametrisation or calibration	Validation	Time horizon	Interaction topology
S57	Lee and Brown, 2021a	Exploring EV adoption	Social class, fuel prices, tariff data, EV attributes, travel attributes	The impact of conventional vehicle sales bans, EV brand availability, BEV with loyalty, BEV without loyalty, PHV with loyalty, BEV with loyalty and CV parity	The UK	Main agent, Battery, Car, Car owner, Household, Charging, Media, Car manufacturer	Theory-driven, Roger's diffusion of innovation model, Consumat framework	Psychological model (Information seeking strategies, satisfaction and uncertainty)	Real-world trip data	Comparing with historical and recent real-world data. Model output validation	Future. Different time steps.	Not specified
S58	Lee and Brown, 2021b	Exploring EV adoption	Socioeconomic, geographical attributes	Cost reductions + price parity	The UK	Car owners, media	Theory-driven, Consumat framework, Behaviour-based EV grid Integration (BEVI) model	psychological model (Information seeking strategies, satisfaction and uncertainty)	UK National Travel Survey	Not specified	Future. From 2010 to 2036	Small-world, homophily index,
S59	Ramsey et al., 2018	Exploring EV adoption	Cost, technical attributes	Playing with costs	Poland, two cities of Wroclaw and Katowice	Household	Heuristic	Based on cost evaluation between EV and CV	Statistics published by the European Automobile Manufacturers Association in 2016	Model output validation	Future, 5 years	Neighbourhood effect
S60	Rodemann et al., 2019	Estimating EV charging demand	Weather, vehicle attributes, charging attributes, driver characteristics	normally distributed charging demands, a minor extension of the basic scenario, stopping using charging infrastructure	A city in Germany	EVs, charging point, drivers	Heuristic	State of charge threshold	Historical data	Not specified	Future. 365 days	Not specified
S61	Schröder and Wolf, 2017	Exploring carsharing adoption	Transportation needs (e.g., safety, comfort, environmental friendliness)	Campaigns corresponding to variables (need nodes)	Berlin, Germany	Individual, social network	Theory-driven, InnoMind simulation	Artificial neural network	A survey ($n = 675$)	Comparing with actual data. Model output validation	Future. 100-time steps	Homophily
S62	Schwoon, 2006	Exploring alternative fuel vehicle adoption	Consumer attributes, producer attributes, infrastructure attributes	Six scenarios including combinations of two tax scenarios along with three infrastructure scenarios	Germany	Consumers	Heuristic	Utility maximization	Data from the Federal Bureau of Motor Vehicles and Drivers (FBMVD), survey data of a sample of some 26,000 German households	Not specified	Future. From 2005 to 2030	Lattice
S63	Segui-Gasco et al., 2019	Exploring ridesharing adoption	Travel demand, vehicle attributes	Diverse AMoD scenarios from different standpoints	London, UK	Travellers, operators, city	Theory-driven, IMSim and MATSim	Utility maximization	National Travel Survey (NTS) and the UK census data	Cordon analysis and travel-time comparison process. Model output validation	Base year	Not specified
S64	Shafiei et al., 2012	Exploring EV adoption	Synthetic population, social demographic groups, vehicle attributes, recharging and range effects	The effects of fuel prices, vehicle taxes, the future price of EVs and recharging concerns	Iceland	Social group	Heuristic, preferences and social influence	Utility maximization	Danish social study data, existing literature	Not specified	Future. From 2012 to 2030	Not specified

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No.	Study	Aim	Variables embedded in the model	Policy scenario[a]	Region	Target agent or population	Conceptual modelling framework[b]	Decision-making process[c]	Parametrisation or calibration	Validation	Time horizon	Interaction topology
S65	Shafiei et al., 2013	Exploring modal shift behaviour	Consumer choice behaviour, energy supply system, fuel stations, vehicle supply	Only base scenario	Iceland	Consumer, Car manufacturer, Car dealer, Vehicle, Energy supply system, Fuel station, Government	Heuristic, integrated system dynamic and agent-based model	Word of- mouth, Utility maximization	Assumed values	Not specified	Future. From 2013 to 2050	Word of-mouth
S66	Shimizu et al., 2014	Exploring bike sharing adoption	Player, station, cost	Hill scenario, commuting scenario, circulation scenario, sightseeing scenario, random scenario, subsidy scenario	Hypothetical region	Individuals (70 agents)	Heuristic, Q learning	Nash equilibrium, game theory	Generated data	Not specified	Base year	Not specified
S67	Shirzadi Babakan et al., 2015	Exploring modal shift behaviour	Demographic, socioeconomic, travel attributes	Construction of a new highway, BRT and subway	Tehran, Iran	Tenant households	Heuristic, multi-objective decision-making algorithm	Multicriteria decision-making method	Population synthesis from the available demographic data	A survey sample of 1485 actual tenant households. Model output validation	Base year	Not specified
S68	Silvia and Krause, 2016	Exploring PHEV adoption	Demographic, socioeconomic, travel attribues, vehicle attributes, innovativeness, environmental attitudes	Reducing vehicle purchase price, expanding the local public charging network, increasing the number and visibility of BEVs	The US	Initial BEV drivers and non-EV drivers	Heuristic	Variables' threshold (8 logical questions)	Empirical data and probability distributions	Based on previous research. Model output validation	Future. 35 years	Not specified
S69	Sopha et al., 2017	Exploring alternative fuel vehicle adoption (natural gas vehicles)	Vehicle attributes, agent attributes	Safety scenario, subsidy scenario, combined scenarios	Indonesia	Consumer	Theory-driven	Utility maximization	Surveys	Data, theory, and model output validation	Future. From 2014 to 2030	Small-world
S70	Stephens, 2010	Exploring PHEV adoption (energy demand and emissions)	Driver attributes, travel attributes, electricity supplier, fuel	PHEV penetration levels, Gasoline price, Constant electricity rate, Time-of-use electricity rates, Charging at home and at work, Arrival time distribution, Distance between home and work	The US	Drivers	Heuristic, Driver Vehicle Use Decision (DVUD) model.	Considering drivers' schedule and travel cost	Statistical information on travel by U.S. drivers, data on the greenhouse gas (GHG) emissions	Not specified	Base year	Not specified
S71	Sun et al., 2019	Exploring EV adoption (effects of public subsidies)	CV and EV attributes (e. g., tank capacity, energy efficiency, gasoline price, battery cost)	Business-as-usual scenario, consumer subsidy and manufacturer subsidy scenarios	the US	Consumer agents and manufacturer agents.	Heuristic	Utility maximization	The data of the U.S. automobile market in 2010, different published papers	Not specified	Future. From 2010 to 2050	Not specified

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No.	Study	Aim	Variables embedded in the model	Policy scenario[a]	Region	Target agent or population	Conceptual modelling framework[b]	Decision-making process[c]	Parametrisation or calibration	Validation	Time horizon	Interaction topology
S72	Sweda and Klabjan, 2015	Estimating EV charging infrastructure	Driver attributes	Effect of Gasoline Prices, Effect of Greenness, Effect of Social Influence, Effect of PEV Prices, Effect of Number of Charging Stations	Chicago, the US	Drivers	Heuristic, Information system, spatial	Variables' threshold	Historical data	Without validation	Future. 10 years	Random
S73	Tran, 2012	Exploring alternative fuel vehicle adoption and modal shift behaviour	Vehicle attributes	Network influence scenarios	International	Individuals	Heuristic	Utility maximization	Mass market – industry survey data	Not specified	Future. 100 and 30-time steps	Small-world
S74	van der Kam et al., 2019	Estimating EV charging demand	EV attributes, location, travel attributes, environmental self-identity, range anxiety	Financial incentives, automated smart charging, information campaigns and social charging	the Netherlands	EV drivers	Theory-driven, environmental psychology	Psychological model	Different datasets such as OViN 2016 dataset	Not specified	Base year	Not specified
S75	Vijayashankar, 2017	Estimating user behaviour and EV charging infrastructure	Travel attributes, EVs and charging infrastructure, charging attributes	Effect of search radius (municipality), Effect of neighbourhood type, charging state,	the Netherlands	Commuter, resident, EVs and CPs, parking, municipality, charge point manufacturer and operator	Heuristic, Charging module of the Agent-based Buying, Charging and Driving (ABCD) model	Variables' threshold	GIS data of these neighbourhoods, real-world market data, OViN data	Expert insights and predictions. Face validation	Future. From 2017 to 2035	Not specified
S76	Vliet et al., 2010	Exploring alternative fuel vehicle adoption	Travel demand and supply attributes	Demand and supply-side interventions	The Netherlands	Motorists, 11 subpopulations	Heuristic, supply and demand models	A heuristics-based decision-making algorithm	Real-world sources	Without validation	Future. 20 years	A simple proxy for social influence
S77	Vooren and Alkemade, 2012	Exploring alternative fuel vehicle adoption and modal shift behaviour	Vehicle attributes, infrastructures	Low environmental concerns, moderate environmental concerns	Hypothetical region	Consumers	Heuristic	Based on infrastructure availability and affordability	Assumed and generated data	Not specified	Future. 100-time steps	Not specified
S78	Vouzavalis, 2020	Exploring EV adoption	Vehicle attributes, costs, prices	Only VW BEV sales, only Toyota BEV sales, only Tesla BEV sales	In Europe and the Netherlands	Consumer, car, dealer	Theory-driven, TPB	Psychological model	Data of manufacturers	Comparing with the real-world operation. Face, and process validation	Future. Yearly, 30 years. From 2020 to 2050	Random
S79	Wolbertus et al., 2021	Estimating user behaviour and EV charging infrastructure	Charging attributes, battery size, maximum walking distance, state (connected or disconnected), purchase decision moment, attitude towards EV, home location	Roll-out strategies concerning charging infrastructures	Amsterdam, The Netherlands	EV drivers, non-EV car owners, charging point operators	Heuristic	Utility maximization	Data of the public charging infrastructure in 2017 (682.709 charging sessions)	The same data from 2018 (1.080.925 charging sessions). Model output validation	Future. From 1st of January 2018 until the 31st of December 2024	Not specified
S80	Wolf et al., 2015	Exploring modal shift behaviour	Demographic, socioeconomic, preferences, motives	Base, Zero-emission zone scenario, Tax exemption scenario, Purchase subsidy scenario	Berlin, Germany	Individuals	Theory-driven, Innovation diffusion driven by changing Minds	Artificial neural networks accounting for the role of emotions	A survey, an online questionnaire (N = 675)	Using statistical analyses. Model output validation	Future. 100-time steps or roughly a period of 20 years	Random, homophily, Blau space

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No.	Study	Aim	Variables embedded in the model	Policy scenario[a]	Region	Target agent or population	Conceptual modelling framework[b]	Decision-making process[c]	Parametrisation or calibration	Validation	Time horizon	Interaction topology
S81	Zhang et al., 2011	Exploring alternative fuel vehicle adoption	Vehicle attributes, cost, price	Implementation of Technology Push, Implementation of Market Pull, Implementation of Regulatory Push	The US	Manufacturers, Vehicle, consumers, and governmental	Heuristic	Utility maximization	Choice-based conjoint data of >7000 respondents, existing literature	Comparing with real data. Theory, face, model output, and process validation	Base year	Random, word of-mouth
S82	Zhuge et al., 2021	Exploring EV adoption (the role of charging technologies)	Demographic, vehicle attributes, environmental awareness	Playing with vehicle price and usage	Beijing, China	Individuals, household, others (e.g., manufacturers)	Theory-driven, SelfSim-EV, Multi-Agent Transport Simulation.	Utility maximization	Two surveys in Beijing from September 2015 to March 2016, some macro data from 2011 to 2014 on vehicle prices, vehicle sales, EV subsidies etc.	The same macro data from 2015. Model output validation	Future. Yearly, 5 years. From 2016 to 2020	Not specified
S83	Zhuge et al., 2019a	Exploring EV adoption	Travel attributes, parking facilities, refuelling behaviour	Base scenario	Beijing, China	Driver	Theory-driven, MATSim, Multi-Agent Transport Simulation.	Utility maximization	The 2010 Household Travel Survey Data and the data on parking and refuelling behaviours were collected in a questionnaire survey in Beijing from September 2015 to March 2016.	Training and validation datasets. Model output validation	Base year	Not specified
S84	Zhuge et al., 2019b	Exploring EV adoption	Environmental awareness, vehicle attributes	Influence of different EV-related policies, technologies and infrastructures	Beijing, China	Consumer, government and manufacturer agents	Theory-driven, SelfSim-EV, Multi-Agent Transport Simulation.	Utility maximization	Two surveys in Beijing from September 2015 to March 2016, some macro data from 2011 to 2014 on vehicle prices, vehicle sales, EV subsidies etc.	The same macro data from 2015. Model output validation	Future. Yearly, 5 years. From 2016 to 2020	Not specified
S85	Zhuge et al., 2020a	Exploring EV adoption	Environmental awareness, vehicle attributes	PHEV Subsidy, petrol prices, electricity price for EVs	Beijing, China	Consumer, manufacturer, government	Theory-driven, SelfSim-EV, Multi-Agent Transport Simulation.	Utility maximization	Two surveys in Beijing from September 2015 to March 2016, some macro data from 2011 to 2014 on vehicle prices, vehicle sales, EV subsidies etc.	The same macro data from 2015. Model output validation	Future. Yearly, 5 years. From 2016 to 2020	Not specified
S86	Zhuge et al., 2020b	Exploring EV adoption (the license plate lottery policy impact)	Environmental awareness, vehicle attributes	The license plate lottery policy	Beijing, China	Consumer, manufacturer, government	Theory-driven, SelfSim-EV, Multi-Agent Transport Simulation.	Utility maximization	Two surveys in Beijing from September 2015 to March 2016, some macro data from 2011 to 2014 on vehicle prices, vehicle sales, EV subsidies etc.	The same macro data from 2015. Model output validation	Future. Yearly, 5 years. From 2016 to 2020	Not specified

Note.

[a] Policy scenario refers to different variants of policies such as price-based or preference-based scenarios.

[b] Conceptual modelling framework refers to stepwise behavioural rules that model can be homogenously or heterogeneously shaped.

[c] Decision-making process refers to how agents in each iteration of the simulation make a transport-related choice.

Appendix C

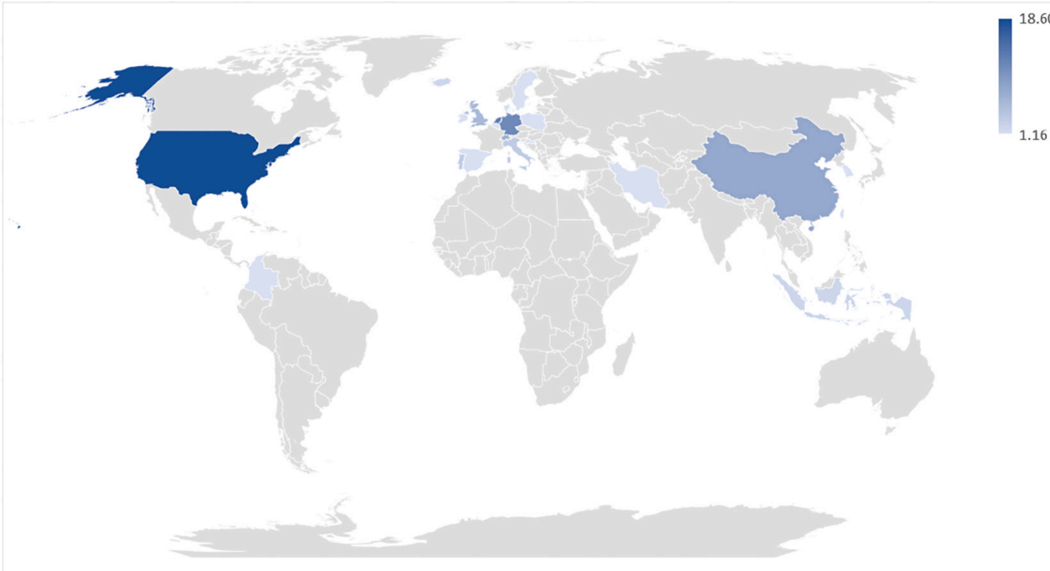

Fig. C. Geographical distribution of case studies.

Appendix D

Table D
Key findings of ABM studies investigating mobility transition.

No.	Study	Key finding
1	Adepetu and Keshav, 2017	EV price is the most significant barrier to EV diffusion
2	Adepetu et al., 2016	San Francisco is an ideal city for EV adoption
3	Ahanchian et al., 2019	Disincentivizing private cars have the largest impact on modal shift
4	Ahkamiraad and Wang, 2018	EV use will result in a large expansion over the next years
5	Arian and Chiu, 2017	Policies should be market-budget oriented
6	Aziz et al., 2018	Widening sidewalks and increasing bike lane network are effective policies for modal shift
7	Basu et al., 2018	Mass transit should be used along with AMoD
8	Brown, 2013	EV share will range from 1 % to 22 % in the year 2030
9	Buchmann et al., 2021	To accelerate e-mobility diffusion Germany needs a more combined package of policies
10	Bühne et al., 2015	EV price is the most significant barrier to EV diffusion
11	Chaoxing, 2017	Various sale schemes can affect EV diffusion
12	Chaudhari et al., 2019	Employing ABMs are very important in forecasting the charging demand of EVs
13	Choi, 2016	Vehicle price change has the greatest impact on the market share of hybrid vehicles
14	Ciari et al., 2016	Proposed carsharing simulation through an activity-based model lens
15	de Haan et al., 2009	Suggesting energy-labelling feebate schemes for car market shares
16	Eppstein et al., 2011	Suggested longer-range lower-cost PHEV batteries
17	Faboya et al., 2020	Intervention could focus on the right travellers' needs
18	Fagnant and Kockelman, 2014	The shared autonomous vehicle has beneficial emissions influences
19	Geerlings, 2020	Technology policy can positively impact the satisfaction of EV consumers
20	Gnann et al., 2015	The maximum share of PEVs in a German passenger car will be 3 % by 2020
21	Gnann et al., 2018	Germany can promote EV uptake without any public charging infrastructure until 2030
22	Hajinasab et al., 2016	Different modal choice patterns are revealed based on different scenarios
23	Hörl et al., 2019	Shared automated mobility may lead to high occupancy rates
24	Hörl et al., 2021	The system effect of automated taxi service was not found positive
25	Huang et al., 2021	Consumers' attitude towards EVs is more negative
26	Huétink et al., 2010	Social network plays the most contribution to the technological trajectory of hydrogen vehicles
27	Hussain et al., 2016	Predicting the long-term impact of carpooling in Flanders, Belgium
28	Inturri et al., 2021	Demand Responsive Shared Transport (DRST) is more effective than a taxi
29	Inturri et al., 2019	The number and capacity of vehicles can significantly impact shared mobility services
30	Kangur et al., 2017	Exclusive support for full battery EVs has the greatest impact on emission reduction
31	Kangur, 2014	Measures at battery EVs should be targeted
32	Kieckhäfer et al., 2014	Neglecting individual behaviour in an aggregated system may lead to wrong estimations on the EV market
33	Kieckhäfer et al., 2017	Manufacturers' portfolio strategies have a strong influence on the EV market
34	Klein et al., 2020	

(continued on next page)

Table D (*continued*)

No.	Study	Key finding
		Technological progress in charging time and range of EVs can noticeably promote PHEV market shares
35	Köhler et al., 2009	Hydrogen vehicles will be common in the near future
36	Köhler et al., 2020	Policymakers should take cultural and behavioural measures on mobility transition issue.
37	Lemoine et al., 2016	ABM can improve the design of public transit infrastructures
38	Liu et al., 2017	Shared autonomous vehicles may be a threat to public transit services
39	Lu et al., 2018	Free use of bike-sharing services is the most sustainable intervention
40	Maggi and Vallino, 2021	A preference-based policy seems more effective than a price-based one
41	Martinez and Viegas, 2017	A shared self-driving service can noticeably reduce CO2 emissions
42	Martinez et al., 2015	A Shared-taxi system may result in noticeable fare and travel time savings
43	Martínez et al., 2016	Carsharing will perform worse than cars in terms of time and cost
44	McCoy and Lyons, 2014	Mild peer influences may result in enormous clusters of EV adopters
45	Mueller and de Haan, 2009	Forecasting the role of policy levers on mobility transition
46	Natalini and Bravo, 2013	A combination of preference and market-based policies should be taken into account
47	Ning et al., 2019	EVs share for student and worker groups will be 35.7 % and 20.8 %, respectively
48	Noori and Tatari, 2016	Government subsidies have the most impact on EVs diffusion
49	Novizayanti et al., 2021	Proposing an initial simulation package modelling EV transition
50	Novosel et al., 2015	Illustrated hourly effect of EV on the energy system
51	Oh et al., 2020	AMoD can noticeably increase traffic congestion if an unregulated introduction is planned
52	Oke et al., 2020	Integration of AMoD with transit led to a better traffic condition
53	Olivella-Rosell et al., 2015	EV charging demand influences distribution networks
54	Pagani et al., 2019	The profitability of uptaking EVs is uncertain in Switzerland
55	Querini and Benetto, 2015	Proposed a life cycle assessment for evaluating mobility policies
56	Querini and Benetto, 2014	Recommended the deployment of charging points + EV awareness campaign
57	Lee and Brown, 2021a	Less wealthy citizens will benefit from EVs
58	Lee and Brown, 2021b	Evaluating the role of social class and income on EV diffusion
59	Ramsey et al., 2018	simulated the uptake of EVs among the Polish community
60	Rodemann et al., 2019	Small changes in external factors can result in large changes in the EV market
61	Schröder and Wolf, 2017	Cost campaign has the leading effect on carsharing
62	Schwoon, 2006	A tax on fossil fuel cars can promote the diffusion of fuel cell vehicles
63	Segui-Gasco et al., 2019	Simulating ridesharing service in autonomous vehicles
64	Shafiei et al., 2012	Suggested a combined scenario of decreased rate of EV price + high gasoline price
65	Shafiei et al., 2013	Forecasting EV market via employing an integrated system dynamic and ABM
66	Shimizu et al., 2014	Simulated willingness to share bikes
67	Shirzadi Babakan et al., 2015	Development of the new subway line has the most effective influence on modal shift
68	Silvia and Krause, 2016	Highlighted the effectiveness of policy options on EV technology
69	Sopha et al., 2017	A psychological model could better explain the adoption of natural gas vehicles
70	Stephens, 2010	Greenhouse gas emissions from the fleet will be decreased by around 26 %
71	Sun et al., 2019	Consumer subsidy is more effective than manufacturer on EVs diffusion
72	Sweda and Klabjan, 2015	Proposed a simulation package for charging infrastructure deployment of EVs
73	Tran, 2012	Network influence can pave mobility transition way
74	van der Kam et al., 2019	Highlighting the role of environmental psychological factors in future simulations
75	Vijayashankar, 2017	Estimated the number of EVs charging points
76	Vliet et al., 2010	Recommended sustained combinations of interventions
77	Vooren and Alkemade, 2012	Policy measures on technological change can change the diffusion of low emission vehicles
78	Vouzavalis, 2020	Consumers' demand and preference for powertrain influence profits of car companies
79	Wolbertus et al., 2021	Highlighting the impact of return to scale and reciprocal effects in charging infrastructures of EVs
80	Wolf et al., 2015	Introducing an exclusive zone for EVs can result in EV adoption
81	Zhang et al., 2011	Technology push is one of the important factors for accelerating diffusion
82	Zhuge et al., 2021	A yearly decrease in battery cost results in increased uptake of PHEV
83	Zhuge et al., 2019a	Developed a complex ABM computing vehicular energy consumption and emissions
84	Zhuge et al., 2019b	The rate of using battery EVs will be increased from 2016 to 2020
85	Zhuge et al., 2020a	Doubling the PHEV subsidy would increase the PHEV sale
86	Zhuge et al., 2020b	A license plate lottery policy can noticeably impact on EVs diffusion

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Milad Mehdizadeh has a background both in civil engineering (transportation engineering and planning) and traffic psychology (environmental psychology). Milad is currently conducting research on travel behaviour, traffic psychology, and how transportation interacts with health, environmental, and safety issues using behavioural modelling. As a researcher, he is specifically working on a project, investigating mobility transition in Norway, funded by Norwegian Centre for Energy Transition Strategies (NTRANS) of Norwegian University of Science and Technology (NTNU). Milad is a full-time employee and member of two research groups at NTNU.

Trond Nordfjaern is a Full Professor in Social Psychology, Department of Psychology, NTNU (2017). He has two doctoral degrees in psychology. Trond has been awarded the scientific prize from the Regional Health Care Enterprise (Helse Midt-Norge RHF) for excellent research among highly prioritized patient groups (2011). He has also been elected a lifetime member of the Royal Norwegian Society of Sciences and Letters Academy (DKNVS) 2020.

Christian A. Klöckner is a Full Professor in social psychology and quantatitve methods at the Norwegian University of Science and Technology. He leads the research group for "Citizen, Environment, and Safety" which is focusing on researching individual, social and contextual drivers of environmental decisions (including food, energy, mobility, housing). His personal research interest are modelling of environmentally relevant decisions and behaviour in the social and structural context, innovative environmental communication methods, societal disruption and transition, and psychologiocal trade-offs in sustainability issues. He is engaged in many national and international research projects, coordinating several of them, among them the H2020 projects ECHOES, SMARTEES, and ENCHANT. He is author of more than 100 academic papers.