Transportation Research Part D 107 (2022) 103278

Contents lists available at ScienceDirect

Transportation Research Part D

journal homepage: www.elsevier.com/locate/trd

Mathematical modelling of electric vehicle adoption: A systematic literature review

Lucy Maybury [a,*], Padraig Corcoran [a], Liana Cipcigan [b]

[a] School of Computer Science & Informatics, Cardiff University, United Kingdom
[b] School of Engineering, Cardiff University, United Kingdom

ARTICLE INFO

Keywords:
Electric vehicles
Emerging technologies
Mathematical modelling
Sustainable mobility
Technology adoption
Transition theory

ABSTRACT

As decarbonisation is becoming increasingly important, many countries have placed an emphasis on decarbonising their transportation sector through electrification to support the transition to net zero. As such, research regarding the adoption of electric vehicles has drastically increased in recent years. Mathematical modelling plays an important role in optimising a transition to electric vehicles. This article describes a systematic literature review of existing works which perform mathematical modelling of the adoption of electric motor vehicles. In this study, 53 articles containing mathematical models of electric vehicle adoption are reviewed systematically to answer 6 research questions regarding the process of modelling transitions to electric vehicles. The mathematical modelling techniques observed in existing literature are discussed, along with the main barriers to electric vehicle adoption, and future research directions are suggested.

1. Introduction

Given the established scientific link between the amount of carbon in our atmosphere and global warming, the reduction of carbon emissions, decarbonisation, is becoming an increasingly important goal. In recent years, many developed countries have made formal commitments to achieving decarbonisation within a specified timeframe, for example, the Paris Agreement (United Nations, 2016), which is an international treaty on climate change by the United Nations. In the UK, its importance is emphasised by the UK government's policies, such as the **Industrial Decarbonisation Strategy**, which outlines how the industry can decarbonise in line with net zero: the balance between the amount of greenhouse gas produced and the amount removed from the atmosphere (HM Government, 2021a). Two countries, Bhutan and Suriname, have achieved carbon neutrality, and many other countries worldwide have a decarbonisation strategy, with Uruguay committing to carbon neutrality by as early as 2030, followed closely by Finland in 2035.

A major aspect of decarbonisation as a whole is the decarbonisation of transport—in 2019, the transport sector was responsible for an estimated 34% of carbon dioxide emissions in the UK (Department for Business, Energy & Industrial Strategy, 2020). Many scientists are campaigning for a transition away from personal vehicles towards a more shared approach, namely public transport. However, Geels (2012) states that "car use is characterised and deeply rooted in an individual's feelings of autonomy and freedom of movement". Therefore, for any transition to be supported by the population, it must maintain this autonomy and freedom of movement. A transition to total public transport without any private vehicles may not achieve this. Thus, a transition from conventional fossil fuel vehicles to alternative fuel vehicles, namely electric vehicles (EVs), is necessary to avoid the total elimination of private vehicles. This is exemplified by the UK government identifying EVs at the heart of its industrial strategy, with the

* Corresponding author.
E-mail address: mayburyle@outlook.com (L. Maybury).

https://doi.org/10.1016/j.trd.2022.103278

Available online 17 May 2022

Road to Zero (the transition to zero-emission road transport) setting the landscape to achieve this ambition (HM Government, 2021b), and the sale of petrol and diesel cars being banned from 2030 in line with the **Ten Point Plan for a Green Industrial Revolution** (HM Government, 2021c). Whilst many countries are mandating the electrification of their transportation systems, the study of EV adoption is important for a number of reasons. After the ban on the sale of new internal combustion engine vehicles (ICEVs), there will likely exist a second hand ICEV market. If the incentives to purchase an EV are poor, many consumers may opt to instead purchase a second hand ICEV for many years following the ban. This would in turn cause a delay in the timely transition to EVs. The study of EV adoption prior to the elimination of new ICEVs can ensure high consumer support of this transition to EVs, meaning that the second hand ICEV market will not hinder the transition to EVs.

The transition to EVs is a technological transition. In other words, it is a major technological transformation in the way the societal process of transportation is fulfilled, and involves changes aside from technological ones, such as "changes in user practices, regulation, industrial networks, infrastructure and symbolic meaning" (Geels, 2002). Therefore, making this transition in an efficient and timely manner represents a challenging problem. There are a number of factors contributing to the difficulty of the transition. For example, the current UK transportation system facilitates ICEVs – vehicles powered by fossil fuels – in terms of infrastructure and maintenance networks. This may cause concerns for EV owners regarding maintenance accessibility. There are also concerns regarding the rate of technology development among EVs and the residual value of the vehicle. Additionally, as technological transitions require a change in user practices, a behaviour change among members of the population is needed. Range anxiety – the fear surrounding the driving range of the vehicle – is common among potential EV users, making it a significant barrier to EV adoption. In particular, range anxiety is related to the vehicle having insufficient range to reach its destination. Specifically, it is associated with battery electric vehicles (BEVs) when they are used to make long journeys of distances which may exceed the driving range of the vehicle. Range anxiety is both a technological and mindset barrier, as more charging infrastructure is needed in order to diffuse it, but EV users also need to become acquainted with the idea that frequent charging is part of mobility, which may be an obscure concept for many. In some situations such as when travelling a long distance, they may need to incorporate the time it takes to charge their vehicle into their daily plan since charging an EV is time consuming in comparison to filling an ICEV with fuel. In other words, the transition to EVs may also be considered a socio-technical transition, in which technology and societal processes are inherently intertwined (Wesseling et al., 2020).

This study provides a detailed overview of existing work on mathematical modelling of EV adoption in the form of a systematic literature review (SLR). Mathematical modelling of EV adoption concerns the use of mathematical concepts and relationships to represent the adoption of, or a transition to, EVs. This definition includes business models with mathematical elements. The application of mathematical modelling to this problem is important because it allows one to formulate and solve associated problems in a scientific manner which draws from existing knowledge and employs best practices. Briefly, a SLR is a type of literature review where the reviewed articles are obtained in a methodical way, and this method was chosen to ensure that this study is comprehensive and that all relevant research in the field is included. Given the recent commitments by many developed countries to achieve decarbonisation as discussed above, this SLR is timely.

This SLR may be a useful resource for two wide audiences. Firstly, academics beginning research in the field may find it useful to read this overview which compares and contrasts existing mathematical models of EV adoption, and may help identify gaps in existing research. If a researcher wishes to model a particular aspect of the problem, this study should indicate which modelling techniques have been used in the past and in turn potentially identify some modelling best practices. It also provides a summary of the data that has been used to parameterise existing models. Secondly, decision makers such as practitioners and city planners may find this study a useful resource in order to gain an overview of the existing state of the art EV adoption modelling techniques. It may provide guidance on how to select a transition policy which results in an efficient and timely transition.

The layout of the remainder of this paper is as follows. Section 2 discusses related literature reviews in this field. Section 3 gives an overview of the SLR process and more specifically documents the data collection process of this study. Section 4 provides answers to the research questions (which can be found in Table 2) by analysing and discussing the collected data. Section 5 gives further insight into the results obtained from the collected data by discussing barriers to EV adoption and gaps in the current field of research. Finally, Section 6 provides conclusions and discusses future research directions following this study.

2. Related work

As decarbonisation through electrification is an important topic at present, there are a number of relevant literature reviews regarding EV adoption. These are summarised in Table 1 and discussed as follows.

Coffman et al. (2015) provide a review of studies concerning factors that affect EV adoption in general, and also studies that forecast EV adoption. Zhou et al. (2016) and Hardman (2019) focus on the adoption of plug-in electric vehicles (PEVs) by investigating studies on non-financial incentives and policy effectiveness respectively. Liao et al. (2017) provide a review of research focusing on consumer preferences for EVs. Hardman et al. (2017) present a SLR of literature regarding the effectiveness of financial incentives for the adoption of BEVs. Coffman et al. (2017) focus on factors affecting EV adoption in general. Austmann (2020) reviews all studies on EV adoption that have employed statistical approaches to analyse actual market data. Vilchez and Jochem (2019) provide a review of system dynamics (SD) models concerned with the market diffusion of EVs. Finally, Kumar and Alok (2020) provide an integrated review of research on the topic of EVs, focusing on topics they deem to have been neglected, such as dealership experience, charging infrastructure resilience, and marketing strategies.

Despite the existence of a number of relevant literature reviews in the field of EV adoption, there is no existing literature review discussing all existing mathematical modelling of EV adoption (to the best knowledge of the authors). As discussed in Section 1, such modelling is becoming increasingly useful as it plays an important role in optimising a transition to EVs. Discussing, comparing and analysing mathematical models of EV adoption is the unique contribution of this study.

Table 1
Literature reviews regarding EV adoption.

Publication	Title	Number of papers reviewed
Coffman et al. (2015)	Factors Affecting EV Adoption: A Literature Review and EV Forecast for Hawaii	Cannot be determined
Zhou et al. (2016)	Plug-in Electric Vehicle Policy Effectiveness: Literature Review	18
Coffman et al. (2017)	Electric vehicles revisited: a review of factors that affect adoption	50
Hardman et al. (2017)	The effectiveness of financial purchase incentives for battery electric vehicles – A review of the evidence	35
Liao et al. (2017)	Consumer preferences for electric vehicles: a literature review	26
Hardman (2019)	Understanding the impact of reoccurring and non-financial incentives on plug-in electric vehicle adoption – A review	41
Vilchez and Jochem (2019)	Simulating vehicle fleet composition: A review of system dynamics models	12
Austmann (2020)	Drivers of the electric vehicle market: A systematic literature review of empirical studies	42
Kumar and Alok (2020)	Adoption of electric vehicle: A literature review and prospects for sustainability	239
This study	Mathematical Modelling of Electric Vehicle Adoption: A Systematic Literature Review	53

Table 2
Research questions.

ID	Question
RQ1	What types of vehicles are considered in the adoption model?
RQ2	What geographical areas are considered in the adoption model?
RQ3	What aspects or variables of EV adoption are modelled?
RQ4	What is the purpose of modelling these variables?
RQ5	What type of model was used?
RQ6	What is the type and source of data used to parameterise the model?

3. Methodology

In this section, the methodology of this study is described. There are a number of advantages of the SLR method. Firstly, there is less chance of excluding an important or relevant article. Secondly, since the research questions are defined prior to the reading of the articles, it is ensured that the necessary information is extracted. This SLR was conducted in accordance with the procedure outlined by Kitchenham (2004). The guidance presented by Weidt and Silva (2016) provides a more specific approach to SLRs for the domain of computer science, and this was also utilised.

3.1. Guidelines

According to the aforementioned guidance, the SLR process consists of 12 steps. These 12 steps were adapted and condensed into 10 steps for the purpose of this study. A brief overview of the adapted 10 steps follows, but full details can be found in (Weidt and Silva, 2016).

(1) Define the research questions. The research questions form the purpose of the SLR, and finding their answers is the motivation behind the study.
(2) Define keywords. In this step, keywords are extracted from the research questions, literature within the field, and the domain knowledge of the authors.
(3) Define the search string. The search string is produced using the keywords and their synonyms. This process is described in Section 3.3.
(4) Selection of search engines. Search engines are chosen in order to find all relevant literature to the study. The search engines chosen must be necessary and sufficient.
(5) String refinement. The search string is tested in the chosen search engines and altered if needed to ensure that the retrieval of all relevant articles is achieved.
(6) Search string execution. The search string is input into the search engines in order to collect results.
(7) Collection of search results. Search results are downloaded and stored using the preferred database system of the authors.

(8) **Define the inclusion and exclusion criteria**. The inclusion and exclusion criteria are defined as guidelines to follow when deciding which of the obtained articles should be included or excluded. This process is detailed in Section 3.4.
(9) **Selection of articles**. The obtained articles are included or excluded by the authors, as detailed in Section 3.4.
(10) **Data extraction**. The included articles are reviewed, and the first author reads the articles in order to collect answers to the research questions of the study.

3.2. Research questions

This SLR was conducted with the main purpose of finding answers to the research questions in Table 2. A brief explanation of each research question follows.

RQ1 considers the type of vehicle that the model focuses on, for example BEVs, hybrid electric vehicles (HEVs), plug-in hybrid electric vehicles (PHEVs), or plug-in electric vehicles (PEVs). The term PEVs refers to the subset of EVs that consists of PHEVs and BEVs.

RQ2 considers the geographical focus of the model in question to identify which continents are well researched in order to pinpoint an area which may need to be the focus of future research. It is also noted whether there is an urban or rural focus, as there are distinctions among the challenges facing EV adoption between these areas. This distinction is discussed further in Section 4.2.

RQ3 has the purpose of identifying which aspects of EV adoption are the focus of existing models, and may identify a gap in the research for future models. The aspects of EV adoption that models may focus on include barriers to EV adoption, policy intervention, and the adoption of specific types of EVs, for example BEVs or PHEVs.

RQ4 determines the purpose of modelling the variables found in RQ3. Examples of the purpose of modelling may be to inform planning decisions, to predict future EV ownership, to understand travel behaviour, to understand perceptions and knowledge of EV technology, etc.

RQ5 aims to determine the technique used to model EV adoption, for example agent-based model (ABM), Markov decision process (MDP), discrete choice model (DCM), system equations model, etc.

RQ6 provides a complete list of the types and sources of data used to parameterise existing models, which could guide the data collection of future studies.

3.3. Data sources and search strategy

A search of all relevant databases is required for a SLR. Therefore the databases Science Direct, IEEE Xplore, TRID and Web of Science were chosen. With the domain expertise of the authors, it was identified that the vast majority of relevant research is published in venues indexed by these databases. In order to ensure all relevant articles were retrieved, a pre-defined search string was input into each of the four databases. The search string consists of three separate terms combined with the Boolean operator 'AND'. Each term focuses on one aspect of EV adoption modelling. The authors used their domain knowledge to combine any relevant terms in each search string using the Boolean operator 'OR'. The process is detailed below.

As this SLR is only concerned with articles involving EVs, the term 'electric vehicle' must be present in the title and/or abstract of any retrieved article. Therefore the first group of terms for the search string is simply a single term: *'electric vehicle'*.

More specifically, this SLR is concerned with articles involving EV adoption. Thus the second group of terms for the search string is defined as follows:

adoption OR transition OR conversion OR adaptation OR shift OR electrification OR forecast OR uptake

Finally, as the purpose of this SLR is to assess different methods of modelling EV adoption, the third group of terms for the search string is defined as follows:

model OR modelling OR simulation OR framework

In order to complete the search string, each group of terms is combined using the Boolean operator 'AND' as follows:

(electric vehicle) AND (adoption OR transition OR conversion OR adaptation OR shift OR electrification OR forecast OR uptake) AND

(model OR modelling OR simulation OR framework)

The search performed by the above specifications on December 7th, 2021 retrieved a total of 147 unique articles. These articles then underwent the selection process.

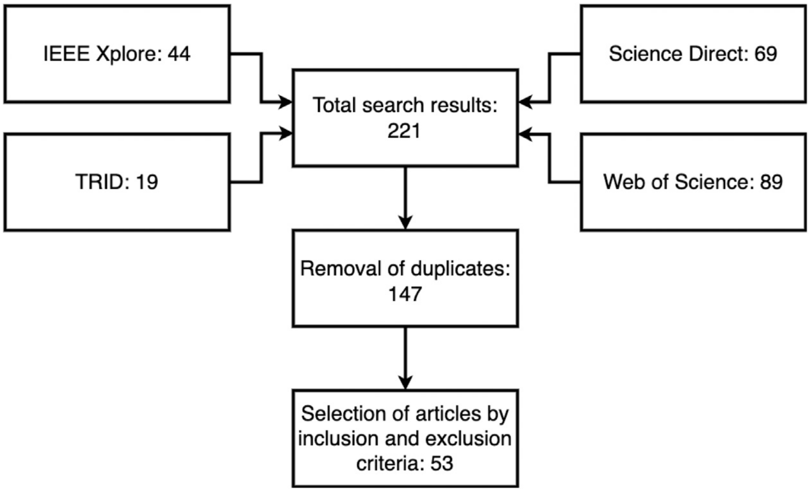

Fig. 1. Article retrieval process.

Table 3
Inclusion criteria.

ID	Criterion
IN1	The article is written in English
IN2	The article must include a model or simulation involving EV adoption
IN3	The article must focus on the transportation aspect of EV adoption

Table 4
Exclusion criteria.

ID	Criterion
EX1	The article is published after 7th December 2021[a]
EX2	The article is not peer reviewed[b]
EX3	The article is a review paper
EX4	The article is not focused on motor vehicles

[a]Articles published after 7th December 2021 are not included because the article collection process for this SLR was completed by this date.
[b]Reports written by organisations are excluded because it is difficult to determine if they have been peer reviewed. Furthermore, such reports are not indexed by publication databases, so reviewing them in a systematic manner is not possible.

3.4. Selection of articles

Of the 92 unique articles retrieved, 42 were selected for review using the specified selection criteria. Of the 42 selected articles, the earliest published article appeared in 2009 while the majority were published from 2017 onward. The inclusion criteria, detailed in Table 3, were used to ensure that all relevant articles were included. The exclusion criteria, detailed in Table 4, were used to ensure that the articles selected were of appropriate quality. The article retrieval process is outlined in Fig. 1.

3.4.1. Biases, disagreements and data extraction

The selection process employed three reviewers in order to ensure an optimal selection of articles. The role of both the first and second reviewers was to independently read the title of each obtained article and decide whether it should be included or excluded from this SLR. In cases of inconclusivity, the abstract was also read. An agreement of 96% was achieved between the first and second reviewer. The reviewers in question are the first and second authors of this article, L. Maybury and P. Corcoran. However, in the case of a disagreement, the third reviewer A. Gagarin independently read the titles (and possibly abstracts) of relevant articles and made the final decision on whether to include or exclude them.

Ultimately, 36% of the obtained articles were approved by the authors. Whilst this approval rate may seem low, EV adoption is an interdisciplinary area, and although the search string was carefully constructed, many articles were rejected as they did not comply with IN3: *The article must focus on the transportation aspect of EV adoption*. In particular, many of the rejected articles focus on the modelling of EV technology, for example (Alamerew and Brissaud, 2020; Al-Tayari et al., 2020; de Luca et al., 2015; Guo et al., 2014).

4. Results

4.1. Articles reviewed

Table 5 provides an overview of the articles reviewed in this study, and simplified answers to the research questions of the study (presented in Table 2). More detailed answers to the research questions are given in Section 4.2.

4.2. Answers to research questions

In this section, more detailed answers to the research questions of this study (presented in Table 2) are provided.

RQ1: What types of vehicles are considered in the adoption model?

Whilst this SLR is concerned with all electric motor vehicles, all articles apart from one focused on electric cars, and one article focused on electric buses.

The majority of the articles did not focus on a particular type of EV, and instead focused on EVs in general. However, there are a number of articles which had a more specific vehicle type focus. Four articles focused on PEV adoption, an additional six specifically on BEV adoption, and an additional one specifically on PHEV adoption. One article focused on HEV adoption, and one article focused on the electrification of buses.

Javid and Nejat (2017) and Tal et al. (2018) created a model to predict PEV adoption. Harbo et al. (2018) used a simulation to predict the effects of PEV adoption on the energy system. Silvia and Krause (2016) aimed to assess the effect of policies on PEV adoption. Eggers and Eggers (2011) chose BEVs for the focus of their model due to the need for a reliable forecasting model after several failed attempts at establishing BEVs. Khazaei (2019) focused on evaluating the factors influencing BEV adoption in Malaysia. Barter et al. (2015) focused on the range and infrastructure barriers to BEV adoption. Jin et al. (2020) focused on understanding BEV carsharing attitudes. Zhuge et al. (2020) simulated the effects of different subsidies on PHEV adoption. He et al. (2014) assessed the influence from social networks on individuals' HEV adoption. Finally, Huang et al. (2012) presented an agent-based simulation framework for the electrification of a public bus fleet.

Eight articles provide a comparison of EVs with ICEVs. Cen et al. (2018) compared the use of EVs and ICEVs for urban commuting in Hong Kong. Karaaslan et al. (2018) compared the effect of EVs and ICEVs on pedestrian safety. Khan et al. (2021) compared BEV, PHEV and ICEV adoption. Liao et al. (2018) compared consumer behaviour before and after the introduction of EV adoption business models. Soltani-Sobh et al. (2016) proposed a model to estimate the modal split between EVs and ICEVs for different states in the US. Nazari et al. (2019) aimed to explain the vehicle type choice of households between BEVs, HEVs and ICEVs. Mulholland et al. (2018) analysed choices of purchasing EVs and ICEVs after EV subsidy removals. Brand et al. (2017) examine the uptake of PEVs by comparing the number of ICEVs and PEVs in a heterogeneous car market in different scenarios.

The work of Shafiei et al. (2017) is unique in the sense that it provides a comparison of EVs with AFVs, more specifically a simulation-based comparison of EVs, hydrogen vehicles and mixed hydrogen electricity vehicles in order to compare possible transition pathways to a carbon-neutral transport sector. It was found that the preferable transition pathway is the transition to a fleet of EVs.

RQ2: What geographical areas are considered in the adoption model?

Continents modelled

The geographical areas modelled are detailed at a continent level in Table 5 and discussed in more detail in this section. There are 17 articles modelling North America, 15 modelling Asia, 13 modelling Europe, 2 modelling Oceania and one modelling South America.

The majority of the articles modelling Asia are focused on China (Feng et al., 2019; Li et al., 2020; Jin et al., 2020; Huimin and Tengyu, 2011) and specifically Beijing (Tal et al., 2018; Liu et al., 2019; Yoon et al., 2019; Zhuge et al., 2020). This could be influenced by the fact that Beijing is considered one of the most polluted cities in China. For example, Liu et al. (2019) chose Beijing for the focus of their model in order to assess how the city smog crisis influences the behaviour of individuals concerning EV adoption. Shankar and Kumari (2019), Prakash et al. (2018) and Kaur et al. (2021) focused on India, which in 2018 was home to 11 of the 12 most polluted cities in the world (WHO, 2018). Both articles focused on investigating barriers to EV adoption in India. Nian et al. (2019) and Huang et al. (2012) focus on Singapore, with the former stating that Singapore is the worst-case market environment for EV adoption due to the absence of incentives. Khazaei (2019) focused on Malaysia and Cen et al. (2018) focused on Hong Kong.

Of the articles modelling Europe, Pasaoglu et al. (2016) modelled the EU as a whole, focusing on the light duty vehicle (LDV) road transport sector, and the rest had more specific focuses. The Nordic countries received attention in the models, with Harbo et al. (2018) modelling Norway, Shafiei et al. (2017) modelling Iceland and de Rubens et al. (2020) modelling the 5 Nordic countries, describing Norway as a global EV leader, Sweden and Iceland as recent intermediate EV adopters, and Denmark and Finland as less developed EV markets. As Ireland and Denmark are reducing EV subsidies, Mulholland et al. (2018) chose these two countries for the focus of their model in order to analyse the long-term effects of said subsidy retractions on EV adoption. Köhler et al. (2009), Tiwari et al. (2020) and Brand et al. (2017) focused their models on the UK, Wesseling et al. (2020) and Köhler et al. (2020) on the Netherlands, Eggers and Eggers (2011) and Massiani and Gohs (2015) on Germany, and Danielis et al. (2018) on Italy.

Table 5
Overview of articles.

Article	RQ1: Vehicle Type	RQ2: Continent	RQ3: Main Aspect	RQ4: Purpose of Modelling	RQ5: Modelling Technique	RQ6: Data Type
Javid and Nejat (2017)	PEVs	North America	Psychological perspective	Predict EV adoption	Discrete choice	Survey
Eggers and Eggers (2011)	BEVs	Europe	Individual-level preferences	Predict EV adoption	Discrete choice	Survey
Feng et al. (2019)	General EVs	Asia	Social commerce	Predict EV adoption	System dynamics	Statistical
Khan and Maoh (2015)	General EVs	North America	Willingness-to-pay	Investigate consumer attitudes	Discrete choice	Survey
Liu and Cirillo (2017)	General EVs	North America	Consumer behaviour	Model purchase behaviour	Discrete choice	Survey
Nian et al. (2019)	General EVs	Asia	The absence of policy support	Investigate EV business models	Business model	Statistical
Kim and Choi (2019)	General EVs	North America	Case studies	Predict EV demand	Technology adoption life cycle model	Case studies
Pasaoglu et al. (2016)	General EVs	Europe	Policy impact	Investigate EV adoption	Combination of agent-based and system dynamics	Statistical
Köhler et al. (2009)	General EVs	Europe	Transition theory concepts	Assess sustainable mobility transitions	Combination of agent-based and system dynamics	Statistical and interviews
Harbo et al. (2018)	PEVs	Europe	Energy system	Predict EV adoption	Agent-based	Statistical
Khazaei (2019)	BEVs	Asia	EV adoption barriers	Evaluate the factors influencing BEV adoption	Structural equation modelling	Survey
Tal et al. (2018)	PEVs	Asia	EV adoption barriers	Suggest ways to increase PEV adoption	Discrete choice	Survey
Liu et al. (2019)	General EVs	Asia	Hazard-related variables	Explore the affects of city smog on attitudes to EV adoption	Protection action decision model	Survey
Wesseling et al. (2020)	General EVs	Europe	Business model design space	Investigate EV business models	Business models	Media sources, academic studies, online databases and government documents
Yoon et al. (2019)	General EVs	Asia	Carsharing	Assess and optimise EV carsharing	Discrete choice	Survey
Barter et al. (2015)	BEVs	North America	Non-cost barriers	Assess non-cost barriers to BEV adoption	Consumer choice	GPS databases
Smith et al. (2017)	General EVs	Oceania	Attitudinal variables	Investigate EV adoption	Hybrid discrete choice	Survey
Shafiei et al. (2017)	Comparison of EVs with AFVs	Europe	Compare hydrogen and electricity transition pathways	Assess sustainable mobility transitions	System dynamics	Statistical
Jia et al. (2019)	General EVs	North America	Fuel tax revenue	Investigate factors influencing EV adoption	Discrete choice	Census
Brozynski and Leibowicz (2020)	General EVs	Cannot be determined	Policymaker's willingness-to-pay	Obtain insights into technology policy decision making under uncertainty	Markov	Cannot be determined
Shankar and Kumari (2019)	General EVs	Asia	Sellers' perspective	Investigate factors influencing EV adoption	Discrete choice	Survey
Liao et al. (2019)	General EVs	Cannot be determined	Battery/vehicle leasing and mobility guarantee	Investigate EV business models	Discrete choice and business models	Survey
He et al. (2014)	HEVs	North America	Social influence	Investigate factors influencing EV adoption	Discrete choice	Survey

(continued on next page)

Table 5 (*continued*).

Article	RQ1: Vehicle Type	RQ2: Continent	RQ3: Main Aspect	RQ4: Purpose of Modelling	RQ5: Modelling Technique	RQ6: Data Type
Cho and Blommestein (2015)	General EVs	North America	EV adoption under different scenarios	Investigate factors influencing EV adoption	Agent-based	Cannot be determined
Köhler et al. (2020)	General EVs	Europe	Multi-level perspective (MLP)	Apply the MLP to the transition to EVs	Agent-based	Empirical
Nazari et al. (2019)	Comparison of EVs with ICEVs	North America	Household vehicle type choice	Predict EV adoption	Discrete choice	Survey and GIS
Cen et al. (2018)	Comparison of EVs with ICEVs	Asia	Urban commuting	Predict EV adoption	Mixed user equilibrium	Survey
Karaaslan et al. (2018)	Comparison of EVs with ICEVs	North America	Pedestrian safety	Investigate the effect of EV adoption on pedestrian safety	Agent-based	Cannot be determined
Pettifor et al. (2017)	General EVs	Global	Policy intervention	Incorporate social influence effects to improve global integrated assessment models	Integrated assessment model	Empirical
Prakash et al. (2018)	General EVs	Asia	Relationship and hierarchy of EV adoption barriers	Investigate factors influencing EV adoption	Interpretive structural modelling	Cannot be determined
Li et al. (2020)	General EVs	Asia	Policy intervention	Investigate factors influencing EV adoption	Small-world network	Statistical and survey
Silvia and Krause (2016)	PEVs	North America	Policy intervention	Investigate factors influencing EV adoption	Agent-based	Statistical
Jia et al. (2020)	General EVs	North America	Factors influencing EV adoption	Predict EV adoption	Machine learning	Survey
Tiwari et al. (2020)	General EVs	Europe	Correlation between socio-demographic profiles with attitudes to EVs	Investigate consumer attitudes	Structural equation	Survey
Mulholland et al. (2018)	Comparison of EVs with ICEVs	Europe	Subsidy retraction	Investigate factors influencing EV adoption	Discrete choice	Statistical
Huang et al. (2012)	Buses	Asia	Bus electrification	Provide a framework for bus electrification	Agent-based	Cannot be determined
Khan et al. (2021)	Comparison of EVs with ICEVs	North America	BEV, PHEV & ICEV comparison	Study the acquisition of EVs in fleets	Discrete choice	Survey
Liao et al. (2018)	Comparison of EVs with ICEVs	Europe	Battery and vehicle leasing	Investigate EV business models	Discrete choice	Survey
de Rubens et al. (2020)	General EVs	Europe	Shortcomings of business models	Investigate EV business models	Business models	Interviews
Zhuge et al. (2020)	PHEVs	Asia	Cost-related factors	Investigate factors influencing EV adoption	Agent-based	Cannot be determined
Jin et al. (2020)	BEVs	Asia	Carsharing	Investigate consumer attitudes of BEVs	Discrete choice	Survey
Soltani-Sobh et al. (2016)	Comparison of EVs with ICEVs	North America	Government incentives	Investigate EV adoption	Discrete choice	Statistical

(*continued on next page*)

Most North America focused articles modelled the US, apart from Khan and Maoh (2015), Khan et al. (2021), which modelled Canada. Kim and Choi (2019), Barter et al. (2015), Silvia and Krause (2016), Jia et al. (2020) and Soltani-Sobh et al. (2016) modelled the US more broadly, whilst some articles had more specific geographical focuses. For example, Karaaslan et al. (2018) used an intersection in Florida, USA for the focus of their simulation to assess the effect of EV adoption on pedestrian traffic safety. Javid and Nejat (2017), He et al. (2014), Nazari et al. (2019) and Ruan et al. (2021) modelled California, Liu and Cirillo (2017) modelled Maryland, Jia et al. (2019) modelled Virginia, and Cho and Blommestein (2015) modelled Oregon.

The articles modelling Oceania (Smith et al., 2017; Higgins et al., 2012), focused on Perth, Western Australia and Victoria, Australia respectively. The single article modelling South America focused on Brazil.

Table 5 (*continued*).

Article	RQ1: Vehicle Type	RQ2: Continent	RQ3: Main Aspect	RQ4: Purpose of Modelling	RQ5: Modelling Technique	RQ6: Data Type
Kaur et al. (2021)	General EVs	Asia	Analysis of technology acceptance	Investigate consumer attitudes	Technology acceptance model	Survey
Brand et al. (2017)	Comparison of EVs with ICEVs	Europe	Consumer segmentation	Investigate factors influencing EV adoption	Discrete choice	Statistical
Danielis et al. (2018)	BEVs	Europe	Total cost of ownership	Predict EV adoption	Discrete choice	Statistical
Higgins et al. (2012)	General EVs	Oceania	Consumer choice	Predict EV adoption	Discrete choice	Statistical
Dong (2018)	General EVs	North America	Charging station placement	Investigate factors influencing EV adoption	Discrete choice	Survey
Yao et al. (2020)	General EVs	Global	Policy intervention	Investigate factors influencing EV adoption	Discrete choice	Statistical
Bitencourt et al. (2021)	General EVs	South America	Policy intervention	Investigate factors influencing EV adoption	Bass diffusion model	Statistical
Ruan et al. (2021)	General EVs	North America	Energy impacts	Other	Agent-based	Survey and GIS
Tian et al. (2019)	BEVs	North America	Charging station placement	Investigate factors influencing EV adoption	Statistical	
Huimin and Tengyu (2011)	General EVs	Asia	Consumers vs manufacturers	Predict EV adoption	Discrete choice	Cannot be determined
Massiani and Gohs (2015)	General EVs	Europe	Variations of Bass parameters	Predict EV adoption	Bass diffusion model	Statistical

Table 6
Purposes of modelling.

Purpose of modelling	Number of articles
Assess sustainable mobility transitions	2
Investigate consumer attitudes	4
Investigate EV business models	5
Investigate factors influencing EV adoption	22
Investigate impacts of EV adoption	2
Predict EV adoption/demand	11
Other	7

The UK's urban/rural divide

There is a clear distinction between the transition to EVs in a rural area compared to an urban area in the UK, detailed in Section 5. Despite this clear distinction between the transition in rural and urban areas, this study finds that most articles do not focus on one or the other specifically, and instead consider a more general transition. Some articles discussed distinctions between EV adoption in rural and urban areas. The model by Jia et al. (2019) predicts that by 2025, an LDV in a rural area will pay an average of 28% more in fuel taxes than an LDV in an urban area. Also, the predicted decline in per-vehicle fuel tax revenue contribution is found to be more significant in urban areas. Karaaslan et al. (2018) observe that pedestrians are more likely to be involved in traffic crashes involving EVs in urban areas.

Only two articles incorporated this urban/rural distinction in their models. Jia et al. (2020) introduced a household-related variable, "urban–rural", that denotes whether the area in question is urban or rural, and thereby describes the impact from the related environment and nearby transportation infrastructure. Mulholland et al. (2018) partitioned the private vehicle consumer market into urban and rural categories using the EuroStat 2014 regional yearbook before further categorisation based on driving profile and class of innovation.

There is no article focusing solely on the transition to EVs in rural areas, but two articles focused their models on urban commuting, with Cen et al. (2018) modelling EV adoption for urban commuting in Hong Kong and Jia et al. (2020) modelling the influence of cost-related factors on EV adoption in Beijing.

RQ3: What aspects or variables of EV adoption are modelled? & RQ4: What is the purpose of modelling these variables?

The transition to EVs is a complex problem consisting of many aspects, therefore most models do not attempt to model every aspect of the problem, and instead focus on a particular aspect or subset of aspects, to suit a specific purpose of modelling. As such, the variables modelled depend on the purpose of modelling. Hence RQ3 and RQ4 are closely linked, and they are answered together in this section.

The articles are categorised into 6 distinct sets of purposes of modelling. Table 6 gives the sets of purposes and the number of articles they contain.

The purposes of models along with the aspects and variables present in the models are discussed in further detail below.

Assess sustainable mobility transitions

As the transition to EVs is a possible option for a transition to sustainable mobility, it is useful to compare it to other sustainable mobility transitions, such as the transition to hydrogen and synthetic fuel vehicles. Two articles assessed sustainable mobility transitions. Köhler et al. (2009) considered environmental variables, cost variables and social structures to identify the conditions for a successful sustainable mobility transition using transition theory concepts. Shafiei et al. (2017) compared the transition pathways to electricity, hydrogen and mixed hydrogen electricity. The main aspects considered are energy markets, consumer choice behaviour, energy supply system, and refuelling infrastructure.

Investigate consumer attitudes

In order to create successful business models for the purpose of increasing EV adoption, it is important that consumer attitudes are understood. Of the four articles with the purpose of investigating consumer attitudes, Khan and Maoh (2015) assessed the willingness-to-pay of EV adopters by considering a number of EV adoption benefits and impediments. Tiwari et al. (2020) assessed public attitudes towards EV adoption by investigating the correlation between these attitudes and socio-demographic profiles. In particular, 10 socio-demographic variables and 24 attitudinal variables were incorporated into the model. Jin et al. (2020) focused on understanding consumer behaviour regarding BEV carsharing, in particular how customers' attitudes affect the BEV sharing population in China. The model included a number of 'level of service' variables, such as the state of charge of the BEV, and policy scenario variables, such as vehicle restriction requirements. Kaur et al. (2021) analysed the effects of consumer knowledge on the adoption of EVs in India by considering the variables of perceived risk and perceived usefulness along with financial incentive policies.

Investigate EV business models

As the lack of successful business models is considered a barrier to wide scale EV adoption, five models have the purpose of investigating EV business models. Nian et al. (2019) propose a business model for use in the absence of policy support whereby the capital cost of EVs can be reduced by approximately 70% of the price of comparable ICEVs. Wesseling et al. (2020) expanded the concept of a BMDS to a socio-technical system, namely the transition to EVs. Liao et al. (2019) investigated consumer preferences regarding two business models, battery/vehicle leasing and mobility guarantee. A comparison of BEVs, PHEVs and ICEVs was provided. The variables considered were general attributes such as purchase and energy cost, BEV specific attributes, and survey respondent variables, along with a PHEV specific attribute, the all electric range, which is the range that the PHEV battery can cover. This PHEV specific attribute was the unique contribution of this study. Liao et al. (2018) assessed the impact of battery and vehicle leasing business models on EV adoption. The respondent variables considered were socio-demographics, current mobility behaviour and vehicle purchase specifications. The mobility guarantee business model was also considered to assess its impact on BEV preference over PHEVs and ICEVs. de Rubens et al. (2020) conducted interviews with experts in the field in order to gain insights into the shortcomings of EV business models. It was found that mobility guarantee is a suitable business model.

Investigate factors influencing EV adoption

Similarly to the motivation for models that predict EV adoption, the models investigating factors influencing EV adoption are important for planning policies that can diminish some of the concerns surrounding EV adoption. A number of articles in this category have specific focuses. Barter et al. (2015) focused on non-cost barriers to BEV adoption by implementing them in the model as additional costs to the customer. The non-cost barriers considered were range and recharging infrastructure limitations. Zhuge et al. (2020) considered cost-related factors influencing PHEV adoption categorised by upfront cost, such as purchase cost, and usage-related costs, such as petrol or electricity costs. Liu et al. (2019), focusing on personal vehicles, investigated the effects of the city smog crisis in Beijing by incorporating hazard-related variables, resource-related variables, stakeholder perception and risk perception, along with the more conventional socio-demographic variables age, gender, income and education level. Brand et al. (2017) assessed the potential impacts of a number of investment pathways and policy intervention on PEV adoption in the UK. Variables incorporated are vehicle attributes for the private user, vehicle attributes for the fleet manager, consumer preferences, willingness-to-pay, and demographic influences.

There are a number of different stakeholders involved in EV adoption, including car manufacturers, governments, and the often overlooked car sellers. As an EV does not need maintenance throughout its life in the same way that an ICEV does, car sellers' lose out on revenue in the sale of EVs, and may be reluctant to transition to EVs for this reason. Shankar and Kumari (2019) explored the enablers and inhibitors of EV adoption intention, specifically from the sellers' perspective. They aimed to investigate which specific factors are crucial for sellers' to transition to the sale of EVs. They incorporated the variables perceived corporate social responsibility obligation and environmental concerns into the model. Pasaoglu et al. (2016) considered LDVs and presented a more general approach in order to show feedbacks and interactions between the main EV adoption stakeholders. They explored the dynamics of the transition to EVs under different oil prices, GDP growth rates, EV component learning rates, subsidy schemes and EU emission targets. The model has over 1500 parameters.

Government policies can incentivise EV adoption, so their effects must be investigated. The following seven articles consider the influence of policy intervention on the adoption of personal EVs. In particular, Soltani-Sobh et al. (2016) examined the connection between EV adoption shares and the presence of government policies incentivising EVs over different US states along with other socioeconomic factors. Silvia and Krause (2016) also examined the impact of policy interventions on the adoption of EVs. Three unique policies were simulated: publicly subsidised reductions of BEV purchase prices, the construction of a public charging network, and the purchase of BEVs as part of government fleets to improve public awareness of EV technology by allowing the public to see more EVs on the roads. Additionally, a hybrid mix of all three policies was simulated. It was found that the hybrid mix of policies is most effective, leading to the greatest number of BEVs on roads. Li et al. (2020) analysed the impact of policy intervention on EV adoption by considering information transmission in a consumer network model. Two consumer attributes were modelled: attitude and behaviour. The unique contribution of this model was the decision-making mechanism. Mulholland et al. (2018) focused on the effects of the retraction of EV subsidies on EV adoption, in particular the retraction of the vehicle registration tax subsidy in Ireland and Denmark. The agents implemented in the model are fuel suppliers, automobile manufacturers, governing bodies and consumers. The variables modelled were tangible costs that are associated with monetary figures, such as purchase cost and maintenance costs, and intangible costs which are difficult to quantify, such as driving range inconvenience and limited charging infrastructure. Brozynski and Leibowicz (2020) obtained insights into technology policy decision making under uncertainty, focusing on policymaker's willingness-to-pay and the costs and benefits of policy intervention. Yao et al. (2020) used econometric methods to analyse the effectiveness of policy intervention for EV adoption in Canada, China, France, Germany, India, Japan, Korea, the Netherlands, Norway, Portugal, Sweden, the UK and the US. The financial variables considered include purchase price, subsidies, sales tax exemptions, VAT exemptions, tax credits, fuel standard, zero emission vehicles mandates, and the target year when the zero emission vehicles sale goal is achieved. The non-financial variables considered include waivers on access restrictions, access to high-occupancy vehicle (HOV) lanes, access to restricted traffic zones, and access to bus lanes. Bitencourt et al. (2021) evaluated the impact of policy intervention on EV diffusion in Brazil by considering two scenarios: the reference scenario, which employs market-based characteristics and assumes the maintaining of current trends, and the alternative scenario, which employs policy intervention in the private car sector.

The role of social influence in technological transitions has been acknowledged in previous literature (Venkatesh et al., 2003). Therefore its role in the transition to EVs has been the focus of two articles. Feng et al. (2019) assessed the influence of feedback interactions on EV adoption. A unique contribution of this study is the incorporation of fuzzy logic, which has the purpose of replicating the cognitive processes of individuals making comparisons. Variables included in the model were cost, infrastructure convenience, vehicle technology, gasoline price, and technology level of EVs. The effect of vehicle technology on decreasing the production cost of EVs was conveyed using the "learning curve" concept. He et al. (2014) aimed to capture the effect of social influence on HEV adoption and integrate this into consumer choice modelling. Variables included in the model were socio-demographics, influence of social networks, vehicle usage, and vehicle specifications.

The placement and number of charging stations is an important factor impacting EV adoption potential. Dong (2018) used a forecasting model to predict the number of charging stations that would be required across the US if every car user was using an EV. The variables considered include state of charge, driving power consumption, battery rated capacity, total mileage, and the distance between the home and destination of the EV user. Tian et al. (2019) focused on BEVs, namely Teslas, and employed a multi-objective programming model to optimise the placement of charging stations in the US by considering the charging variables: charging station service coverage, number of vehicle charging needs per zone, charging time, along with the general variables of user needs, environmental conditions, regional status and level of economic development.

The final five articles in this category aimed to more generally identify barriers to EV adoption. Khazaei (2019) evaluated the factors influencing BEV adoption in Malaysia and implemented the following variables: intention of use of BEVs, facilitating condition, range anxiety, perceived enjoyment, social influence, and environmental concern. Prakash et al. (2018) focused on barriers to EV adoption in India. They aimed to identify a set of barriers to EV adoption in India and find the relationships and hierarchy among these barriers. Smith et al. (2017) focused on personal vehicles and considered a number of explanatory variables such as purchase price, driving range, charging time, availability of charging stations, running costs, engine size, emissions, battery capacity and noise level, and a number of socio-demographic variables such as income, age, education and the number of vehicles per household. There were also attitudinal variables such as environmental concerns, excitement for new technologies, perceived usefulness and subjective norms, which is a unique contribution of this study. Cho and Blommestein (2015) investigated the adoption of EVs under different scenarios by altering the variables: influence on customers, including advertisement from automakers and word-of-mouth influence; consumer variables, such as income; and major variables such as incentives, fuel price and EV price. The main contribution of this study is to show how "emergence of diffusion" results from the interactions of heterogeneous agents, and it is aimed to aid decision makers in understanding the environment of EVs. Tal et al. (2018) investigated barriers to BEV adoption in Beijing by considering vehicle attributes, socio-demographics attitudes and the social system which includes external influences such as charging infrastructure and political conditions, and internal influences which were measured as the behaviours of acquaintances and neighbours in the community.

Investigate impacts of EV adoption

As EVs have implications that differ from those of ICEVs, two articles had the purpose of investigating the impacts of EV adoption. Jia et al. (2019) investigated the impacts of EV adoption on fuel tax revenue in a case study in Virginia, USA. The variables considered were: county demographics including total population, age distribution and sex ratio; household attributes including household size and income; and commute characteristics including commute time and mode. Karaaslan et al. (2018) investigated the effects of EV adoption on pedestrian safety by simulating a traffic intersection in Florida, USA. The agent-based parameters of this model were ambient sound, ambient illumination, ICEV flow rate and EV flow rate. The first two parameters, along with vehicle sound level and vehicle speed, determined the auditory vehicle detectability, which is used to assess the risk a vehicle poses to pedestrians.

Table 7
Modelling techniques.

Modelling technique	Number of articles
Agent-based model	11
Bass diffusion model	2
Business model	4
Discrete choice model	22
Integrated assessment model	1
Machine learning	1
Markov model	1
Structural equation modelling	3
System dynamics model	4
Other	6

Predict EV adoption/demand

In order to plan for suitable infrastructure, energy and policies, it is necessary to predict EV adoption/demand. Javid and Nejat (2017) predicted EV adoption in California with the motivation to reduce greenhouse gas emissions by means of the 'replace' strategy, whereby ICEVs are replaced with BEVs and PHEVs. Consumer behaviour and ethics were considered, with this psychological perspective being the unique contribution of the study. Eggers and Eggers (2011) predicted the number of early EV adopters over the next 10 years in Germany based on individual-level preferences. It is said to give decision makers a good basis for evaluating prices of EVs and product management options to enhance EV acceptance. Kim and Choi (2019) predicted the demand of EVs in the US based on a number of case studies. Harbo et al. (2018) predicted the number of EVs to understand how EV adoption will impact the energy system in Norway. The model simulated the power demand of EVs in a given area. Nazari et al. (2019) aimed to address one of the main gaps in EV adoption models which is the rare use of revealed preference (RP) datasets to predict EV adoption. RP datasets are based on actual behaviour. Cen et al. (2018) predicted how the EV market will evolve under a number of different circumstances in an urban setting. The model categorised EVs into those with and without immediate charging need. The latter behave similarly to ICEVs. The variables considered were purchase price, driving range, detour time and cost. Jia et al. (2020) predicted regional EV adoption in the US by exploring the factors that are associated with EV adoption. The variables modelled were categorised into household-related, social, person-related and travel patterns. Danielis et al. (2018) recognised that Italy has a low uptake of EVs and therefore constructed a total cost of ownership model to evaluate BEV diffusion in Italy. Total cost of ownership refers to all costs related to the EV user. Higgins et al. (2012) considered a number of consumer related variables to examine the uptake of EVs in Victoria, Australia. Variables considered include household type, vehicle type (ICEV or EV), expected vehicle lifespan, ownership of house, household income, and number of vehicles. Huimin and Tengyu (2011) considered both the consumers and manufacturers, and the influence of a number of variables on the decisions of both, to predict the diffusion of EVs. Variables considered include prices, maintenance costs, production costs, market demand and supply. Massiani and Gohs (2015) systematically compared parameters in the Bass diffusion model, namely the p and q parameters, to predict the diffusion of EVs in different market scenarios.

Other

A number of articles had purposes that did not fit into any of the aforementioned categories. Liu and Cirillo (2017) aimed to model EV purchase behaviour and forecast future preferences. Variables considered were fuel prices, electricity prices, vehicle size and price, driving range and fuel economy. Yoon et al. (2019) assessed the potential EV carsharing demand in Beijing. The model was parameterised by demand parameters such as mode split and trip characteristics, recharging/refuelling time, and a number of socio-demographic variables. They aimed to find the optimised carsharing fleet size and optimal vehicle fuel type (ICEVs or EVs). Khan et al. (2021) aimed to study the acquisition of EVs in fleets by considering four latent fleet operating entity variables: BEV leaning, EV sceptical, EV averse and ICEV oriented. Pettifor et al. (2017) aimed to improve global integrated assessment models by extending their ability to provide policy-relevant analysis of real-world processes. Four adopter groups were considered and distinguished from each other by risk aversion and market share. A linear function was modelled which captured the effect of propensity to purchase an EV. Köhler et al. (2020) applied the multi-level perspective (MLP) to gain understanding of the transition to low carbon transport. The MLP is a transition framework consisting of three levels: landscape, regime and niche. The landscape is where global trends which influence and pressure the regime occur. The regime is mainstream society and is supported by social norms. The niche is where new ideas are allowed to grow until they challenge the existing regime. Ruan et al. (2021) considered vehicle specific variables such as vehicle dynamics, flow of power/energy, batteries, motor/generator characteristics, regenerative braking and auxiliary devices with the purpose of analysing the energy impacts of EV adoption. Finally, Huang et al. (2012) aimed to provide a framework for the electrification of public bus fleets.

RQ5: What type of model was used?

A number of different techniques are employed to model EV adoption. Table 7 gives the number of articles employing each modelling technique.

The above modelling techniques are discussed in detail below. Where possible, it is also noted which softwares were used to implement the models in question.

Agent-based models (ABMs) are computational models by which simulations are used to study interactions between individual agents. They can be used to simulate different scenarios and analyse how the agents react to the scenarios.

Harbo et al. (2018) implemented an ABM in Java, simulating 1500 agents over 10 days to gain insights into how the rising adoption of EVs will impact the energy system. Cho and Blommestein (2015) implemented an ABM in NetLogo to perform various scenarios in an artificial society to investigate the adoption and diffusion of EVs under these different scenarios. Silvia and Krause (2016) also used NetLogo to simulate different policy scenarios and assess their impact on PEV adoption. Köhler et al. (2020) utilised the MATISSE model, which is an ABM which allows the application of the MLP. Karaaslan et al. (2018) used AnyLogic software to implement a 3D traffic micro-simulation of an intersection in order to investigate the effect of EV adoption on pedestrian safety. Huang et al. (2012) used an agent-based, multi-paradigm modelling approach to analyse the electrification of a public bus depot. Zhuge et al. (2020) used an agent-based integrated micro-simulation model, SelfSim-EV, to investigate the influence of cost-related factors on EV adoption. Ruan et al. (2021) used the Simulation for Urban Mobility (SUMO) software to run an ABM to monitor the energy consumption of EVs. Huimin and Tengyu (2011) simulated a virtual country with ten thousand cars to replicate the process of electrification and assess the uptake of EVs with the consideration of consumer decisions. Pasaoglu et al. (2016) and Köhler et al. (2009) combined an agent-based approach with an SD structure.

SD modelling is a technique which allows the understanding of the non-linear behaviour of complex feedback systems over time using the following: stocks, flows, internal feedback loops, table functions and time delays. It is said to be an appropriate technique for modelling EV adoption because it is efficient at capturing the delay effect of structures on system behaviours meaning the delay effect of infrastructure construction on EV price can be determined (Feng et al., 2019). Shafiei et al. (2017) created a SD model of Iceland's energy system using UniSyD_IS model, a partial equilibrium SD model which gives a detailed representation of energy resources and technologies, and can capture the interactions among supply sectors, energy prices, infrastructure development and fuel demand. Feng et al. (2019) used SD modelling to evaluate how feedback interactions influence EV adoption. They incorporated fuzzy logic to more realistically replicate the cognitive process of individuals' decision making.

Business models have the purpose of addressing the interests of all stakeholders simultaneously. In the case of EVs, a successful business model should address both the upfront purchase price, and the need to reduce vehicle population growth whilst satisfying tax revenue streams (Nian et al., 2019). The lack of successful business models is considered a barrier to EV adoption. As such, 4 articles focused on business models.

Nian et al. (2019) introduced a new business model for encouraging EV adoption in the absence of policy support. The proposed business model lowers the upfront purchase price for buyers and maintains profitability for dealers and tax revenue streams for the government. Wesseling et al. (2020) applied business model design space (BMDS) to socio-technical transitions in the case of EVs. Liao et al. (2019) compared the performance of two business models. The first business model, battery/vehicle leasing, aims to remove the barrier of purchase price. Instead of purchasing a vehicle, consumers have exclusive access to a vehicle for a certain period of time. The second business model, mobility guarantee, aims to address the barrier of range anxiety. A substitute ICEV is provided on a certain number of days per year to cover any long trips. de Rubens et al. (2020) investigated EV business models by conducting interviews with experts in the field. Each interview was coded in NIVIVO for analysis.

Two articles used the Bass diffusion modelling technique, which is a technique based on a differential equation conveying the adoption of new products. Bitencourt et al. (2021) used the Bass diffusion model to assess the effects of policies on EV sales. The Bass diffusion model is applied in three stages: public policies, economic analysis and market analysis. Massiani and Gohs (2015) also used the Bass diffusion model to portray market diffusion scenarios by systematically comparing different Bass p and q parameters.

The most frequently observed modelling technique among the articles is discrete choice modelling (DCM). In DCM, decision makers choose among a set of mutually exclusive alternatives. These decisions are assumed to be based on maximising utility. 22 articles used a number of different discrete choice techniques.

A number of articles used logistic regression modelling. Nazari et al. (2019) used a combination of a two-level nested logit (NL) model and a mixed logit (ML) model. Javid and Nejat (2017), Tal et al. (2018) and Yoon et al. (2019) used a multinomial logit (MNL) model. Liu and Cirillo (2017) used a combination of a dynamic discrete choice and a MNL model. Brand et al. (2017) used a MNL model to assess the uptake of PEVs from a consumer perspective. Jin et al. (2020) and Liao et al. (2019) used a combination of a hybrid choice model and a MNL model. Smith et al. (2017) also used a hybrid discrete choice model. Eggers and Eggers (2011) used a choice-based conjoint adoption model. Jia et al. (2019) used a bivariate count model. Soltani-Sobh et al. (2016) employed an aggregated binomial logit share model with the annual share of EVs as the dependent variable (with a value between 0 and 1). The software SAS was used to estimate the intercept of coefficients in the model. Yao et al. (2020) used multiple linear regression analysis on panel data to analyse policy impact on EV uptake.

Shankar and Kumari (2019) used a dual-factor model in order to explore the enablers and inhibitors of EV adoption simultaneously. To explore the enablers, the theory of planned behaviour (TPB) was incorporated, which consists of 3 factors. The first factor is the attitude of individuals, which impacts intention to adopt. Second is subjective norms, which is the perceived societal pressure to adopt or not to adopt. Third is perceived behavioural control, which is the perceived ease or difficulty associated with adopting. To explore the inhibitors, the status quo bias (SQB) was incorporated, which is a cognitive bias: a preference for the current state of affairs as opposed to a change. It was used to explore sellers' resistance towards adoption.

Khan et al. (2021) used a latent class model, which is said to offer a better explanation of the behaviour of decision makers when compared to the MNL and ML models. It reveals preference heterogeneity with reference to latent classes existing within the sampled population. Liao et al. (2018) used a latent transition analysis approach, which is an extension of the latent class modelling technique which uses longitudinal data to observe the behaviour of the classes over time. The model assumed that the population consists of several unknown groups with internal homogeneous preferences which differ among groups. The software Pythonbiogeme was applied for the estimation of the latent class model and the software Latent GOLD was applied for the latent class choice model estimation and class assignment of respondents. The software Mplus was applied to estimate the class membership model and latent transition model.

He et al. (2014) introduced a social network simulation into a discrete choice model to capture the dynamic influence from social networks on consumer behaviour regarding EV adoption. Mulholland et al. (2018) implemented a non-linear consumer choice model in Excel. A model entitled CarSTOCK was linked with the consumer choice model, which is a simulation of the private car sector. This indicates the cost and potential effectiveness of policy interventions in the form of well-to-wheel CO_2 emission savings. Non-linear regression was performed with intangible costs as dependent variables and the number of AFVs available in each country as explanatory variables. Cen et al. (2018) implemented a mixed user equilibrium model whereby EVs are divided into two categories: those with and without immediate charging need. This model is said to overcome a limitation of DCMs by considering the placement of charging stations which is usually left out of existing DCMs. Barter et al. (2015) used a consumer choice model to implement three approximations of non-cost limitations of BEVs. These limitations were categorised as follows: the penalty approach, where range and recharging limitations are expressed as additional costs; the threshold-rental approach, where customers are restricted to vehicles that do not exceed a certain number of inconvenienced days per year; and the threshold-household approach, which assumes there is another non-EV in the household available for use on inconvenienced days. Khan and Maoh (2015) used a stated-preference approach to analyse behavioural willingness-to-pay data. Danielis et al. (2018) used a probabilistic total cost of ownership model. This model is used to evaluate the uptake of BEVs in Italy. Higgins et al. (2012) combined choice modelling with multi-criteria analysis to assess the diffusion of EVs. Multi-criteria analysis is the analysis of decisions where there are a number of conflicting possible criteria.

Structural equation modelling (SEM) is a set of modelling techniques by which aspects of a phenomenon are categorised by relations to each other in a structure: a system of equations. Its advantages over regression modelling are that it allows simultaneous evaluation of model construct relations using covariance analysis and it enables bi-directional relationships between variables. In the case of SEM applied to EV adoption, Tiwari et al. (2020) found relationships between socio-demographics and attitudes by investigating the correlation between these variables. Similarly, Khazaei (2019) analysed the factors influencing EV adoption in Malaysia using SEM. Prakash et al. (2018) employed an interpretive structural modelling (ISM) approach, which is useful for finding hierarchies among factors, to find which barriers to EV adoption are most prevalent in India.

A number of unique approaches to modelling EV adoption are observed among the articles. For example, integrated assessment models (IAMs) link main features of society/economy and the atmosphere into a single modelling framework. Pettifor et al. (2017) applied global IAMs to extend their ability to model social influence in the transition to EVs. Jia et al. (2020) used machine learning methods and logistic regression to build an EV adoption prediction model. Logistic regression is then applied to explore EV adoption behaviour. Brozynski and Leibowicz (2020) employed two Markov models to technology transitions to gain insights into technology policy decision making under uncertainty. Markov models are stochastic models used to model pseudo-randomly changing systems (Gagniuc, 2017), and can represent the diffusion or development of a technology. The two models employed were a Markov reward process (MRP), in which technology intervention incurs a one-time upfront cost, and a Markov decision process (MDP), in which technology policy incurs a cost each time the process is in a state which is a target of the policy.

There are six distinct techniques that do not belong to any of the categories considered above for modelling EV adoption. Kim and Choi (2019) used the technology adoption life cycle model to predict the demand of EVs. The technology adoption life cycle model is a sociological model to describe the adoption of a new technology, in this case the adoption of EVs. Liu et al. (2019) applied the protective action decision model, which implements hazard-related attributes and has specific applications in assessing the effects of environmental hazards and disasters on people's decision making. In this case, it was applied to assess the effects of the city smog crisis on individuals' attitudes to EV adoption in Beijing. Li et al. (2020) used a social network model with a decision-making mechanism to consider information transmission in an analysis of the impact of policy intervention on EV adoption. Kaur et al. (2021) applied the technology acceptance model to analyse how EV buyers accept and use EVs. Tian et al. (2019) used a multi-objective optimisation programming model to optimise the placement of EV charging stations in the US. Dong (2018) used quantitative forecast modelling to predict the number of charging stations required in the US to accommodate for the case where everyone has an EV.

RQ6: What is the type and source of data used to parameterise the model?

Table 8 gives the types of data that have been observed in the articles and the number of articles using them, and the types and sources of data are discussed in detail to follow.

The most frequently observed data type among the articles is survey data. A number of articles used data from pre-existing survey-based datasets: Javid and Nejat (2017) used the 2012 California Statewide Travel Survey, He et al. (2014), Dong (2018) and Jia et al. (2020) used a National Household Travel Survey and Tiwari et al. (2020) used survey data from the UK Data Service regarding public attitudes towards EVs.

Stated preference (SP) surveys collect data based on choices made by respondents in hypothetical scenarios. Therefore it is important that questions are worded in a way that does not influence the respondents towards a certain answer. In other words, it is important to minimise bias. Khan and Maoh (2015), Liu and Cirillo (2017) and Cen et al. (2018) used stated preference survey data in their models. Smith et al. (2017) administered a best–worst (B–W) design adaptation of a stated preference survey to 440 households, in which respondents selected their most preferred and least preferred option of four vehicle types: EV, PHEV, Diesel or Petrol. The survey was designed to obtain attitudinal information, vehicle choice decisions and socio-demographic characteristics. Liao et al. (2019) incorporated a stated preference experiment in their survey.

Table 8
Types of data.

Data type	Number of articles
Case studies	2
Empirical	2
GIS or GPS database	3
Government documents	1
Interviews	2
Statistical	17
Survey	23

There are a number of limitations concerned with using SP data, discussed further in Section 5, which can be overcome by the use of RP data. Khan et al. (2021) used a mixture of revealed and stated preference data based on surveys from over 1000 fleet operating entities (FOEs). As SP data is based on attitudes and perceptions, it carries biases into models which have latent variables. To overcome this, the RP data (obtained from the Canadian Fleet Acquisition Survey (CFAS)) was used to parameterise the latent class model. Nazari et al. (2019) recognised that the lack of use of RP datasets is a gap in EV adoption modelling, and hence used a RP dataset from the California National Household Travel Survey 2013–2014 to parameterise their model. They also incorporated the number of charging stations into their model using a GIS database. Ruan et al. (2021) also combined survey data from city of California to input traffic counts along with GIS roadway network data from OpenStreetMap.

Jin et al. (2020) conducted a five part survey. The first part collected the socio-demographic characteristics of the respondents, such as age, income, education level, occupation, living area and working area. The second part collected information regarding the driving profile of the respondent, such as status of vehicle ownership and driving licence status. The third part was related to travel patterns, the fourth part on attitudes towards BEV carsharing, and the fifth part on adoption intention of BEV carsharing.

Eggers and Eggers (2011), Tal et al. (2018) and Liao et al. (2018) collected data in online surveys and Shankar and Kumari (2019), Kaur et al. (2021) and Yoon et al. (2019) collected data in pen-and-paper surveys. Khazaei (2019) distributed 500 questionnaires to postgraduate students, university lecturers from the University Technology Malaysia and top to low level managers from five different companies in Malaysia. Liu et al. (2019) collected data from 482 EV customers in Beijing with a four part survey. Part one introduced the survey and expressed appreciation to the participants, part two explained the scenario regarding EVs, part three presented specific items reflecting multiple scales of constructs and part four presented questions to obtain the socio-demographic characteristics of the respondents.

A number of articles use statistical data to parameterise the models. Feng et al. (2019) used 2013 statistical data in China. Nian et al. (2019) used data from the Singapore Land Transport Authority (LTA, 2004) to incorporate the annual average mileage of cars into the model. Li et al. (2020) used statistics from the China Association of Automobile Manufacturers (CAAM). Silvia and Krause (2016) base the income of model agents on US census data. Mulholland et al. (2018) made a geographical split using EU urban–rural typology from Eurostat, and chose agent age groups from census population data.

Köhler et al. (2020) parameterised their model with empirical data for the Netherlands from StatLine, which is a statistical database on the Dutch Economy and Society. Jia et al. (2019) developed their bivariate count model with vehicle registration data in 132 counties, taken from the Virginia Department of Motor Vehicle, US Census Bureau, and Alternative Fuels Data Center in the U.S. Department of Energy. The data from the Alternative Fuels Data Center is also included in the predictor variables, which report the EV charging infrastructure by county. The dataset also provides information for public charging stations in the US, such as their locations, opening dates, and their number of charging ports. Demographics forecasts are obtained from the Weldon Cooper Center for Public Service, and the household and commute variables are forecasted from historical trend-lines in Census data.

A number of articles obtained information to complement their models by conducting interviews with experts in the EV industry. The article by de Rubens et al. (2020) was based on interviews of length 30–90 min with 257 experts in the transportation and electricity industries. Köhler et al. (2009) also conducted interviews with experts to obtain data on aspects of sustainability transitions that are not documented or easily obtained from existing literature and statistics. Their model was also parameterised with UK transport data. Wesseling et al. (2020) compiled a database to map out the socio-technical system of EVs in the Netherlands using media sources, academic studies, online databases and government-commissioned studies. They also conducted interviews with 17 experts on EV development to better understand the socio-technical system of EVs.

5. Discussion

There are a number of barriers to EV adoption. In this section, the main barriers to EV adoption are discussed, gaps in the research are identified, and future research directions are proposed.

Economic barriers

The first economic barrier emerging from the reviewed literature is that few successful business models to facilitate EV adoption exist. A transition to EVs can be more easily made if supported by the private sector through investment in research and development, and the building of infrastructure, such as charging stations, to support EVs. Such support is only possible if there exists a business model which these organisations can use to ensure a return on their investment. Furthermore, the transition to EVs will require a large upfront expense for users since there currently exists a limited second hand EV market and therefore most potential users will have to purchase completely new vehicles. The transition will also be expensive for governments who will need to invest in building infrastructure to support EVs (e.g. the building of charging facilities and services for drivers waiting for their vehicles to charge). This investment must be optimised, meaning the cost must be minimised whilst simultaneously maximising the payoff, where the payoff is EV adoption. As discussed above, through the development of new business models which draws in additional investment from the private sector, the cost to governments may be reduced. In conclusion, there exists scope for new impactful research on how best to incorporate business models into mathematical models of EV adoption.

The cost of an EV is also considered a significant barrier according to the reviewed literature, with a number of articles focusing models on cost-related factors (Zhuge et al., 2020; Danielis et al., 2018). At present, in the year 2022, there is a scarce second-hand EV market, meaning that most EV purchases are brand new. Furthermore, as we are currently entering an era of high inflation (US Bureau of Labor Statistics, 2022), this barrier may become even more relevant, so there is scope for additional models to tackle it.

Environmental barriers

Whilst EVs are considered a solution for decarbonising many transportation sectors, there are concerns surrounding the source of energy used to charge the vehicles, and whether this energy is coming from renewable generation. There is scope for further research for charging EVs from renewables. There is also concern surrounding battery disposal, and the ability to recycle EV batteries will improve public perception of EVs, hence aiding EV adoption. For example, some applications are looking to use second-hand batteries from EVs as stationary batteries in charging stations as part of the circular economy (Ahuja et al., 2020).

Another environmental barrier to EV adoption is renewable energy storage. Whilst the generation of energy by burning fossil fuels can be manually turned on and off, this is not the case with renewable energy. For example, the stochastic output of wind turbines and solar panels is posing significant challenges to the Electricity System Operators. Therefore, the role of storage is vital for achieving the balance between generation and demand. Further research in the area of renewable energy storage is important in improving public perception surrounding the transition to EVs and the perception of their green credentials. One promising potential solution to this challenge is Vehicle-to-Grid (V2G) technology which would provide greater capacity to store and transport energy when and where it is needed (Bibak and Tekiner-Moğulkoç, 2021).

EV adoption and the UK's urban/rural divide

There are a number of factors indicating that a transition to EVs may be more difficult to achieve in rural areas of the UK. Due to the lack of public transport, the rural population is more reliant on private transport—in 2017, public transport modes accounted for 4% of rural trips, compared to 18% of urban trips in England (Department for Transport, 2017). Also, people in the most rural areas travelled approximately twice as far on average than people in urban areas. These factors suggest that car owners in rural areas tend to drive longer distances than those in urban areas. Whilst charging at home is more readily available to those living in the countryside, these residents may need to travel to cities and other destinations which may be a long distance from their home. Such journeys may introduce the need to charge the EV before returning home, necessitating the need to use a charger other than their home charger. Furthermore, public charging in rural areas is necessary to facilitate the travel of non-residents through these areas, for example tourists travelling to remote areas of natural beauty.

The number of charging stations in rural areas is small. For example, The EV Charging Strategy for Wales (Welsh Government, 2021) is considering a priority for fast charging installation, particularly in rural areas, to overcome the range anxiety and promote confidence in EV adoption.

The combination of driving longer distances and lack of charging stations may lead to range anxiety amongst rural EV adopters. Thus the driving range of EVs may be more of a concern in rural areas than in urban areas. Also, in rural areas there is a higher proportion of older people than there is in urban areas (Department for Environment, Food and Rural Affairs, 2020). Therefore the average person in a rural area may be less susceptible to adopting a new technology.

As stated in Section 4, most reviewed articles do not focus on a transition to EVs in either an urban or a rural area, and instead focus on the transition more generally. This may indicate that there is a gap in the field of research for models focusing specifically on the transition in urban areas or the transition in rural areas. There may also be scope for a model to focus on the transition in both urban and rural areas simultaneously by accounting for the aforementioned distinctions between the two areas in the model. This could help ensure that no group of people is disadvantaged in the transition to EVs due to the type of area that they live in.

Although the above discussion exclusively considers the UK, many of the points mentioned generalise to other developed countries.

Noise emissions

The lack of noise emissions from EVs is considered a positive characteristic as it reduces noise pollution, which is especially useful in urban areas. On the other hand, it may also be considered a barrier to EV adoption, as some pedestrians and cyclists may rely on the noise emitted from vehicles to indicate their presence and safely navigate streets. Despite this, this SLR found that only one article considered the lack of noise emissions from EVs: Karaaslan et al. (2018) considered the variable auditory vehicle detectability, which they used to assess the risk a vehicle poses to pedestrians. Note that some recent works have found that equipping EVs with devices which generate synthetic sounds can help to mitigate the above dangers (Moore et al., 2020).

There exists potential for future research which models the relationship between the level of EV noise emissions and the number of pedestrian and cyclist fatalities or accidents. For example, such models could be used to determine an optimal noise level for EVs in order to make the transition to EVs fair for all, including those who rely on noise emissions for safe navigation.

SP vs RP data

As mentioned in Section 4, there are a number of pros and cons to using SP data and RP data. As SP is based on hypothetical choices, these choices may not always reflect actual behaviour of respondents. This is known as hypothetical bias (Murphy et al., 2005). It is also difficult to capture the complexities of choice decisions without overwhelming the respondents with information. RP surveys can overcome these limitations as they are based on actual behaviour of respondents (de Corte et al., 2021). However, the use of RP data introduces further limitations. When modelling future EV adoption, innovators and early adopters are the only subsets of people present in the RP data. Therefore, RP data is biased towards innovators and early adopters, who often have different motivations for adoption compared to other groups of adopters. Therefore, sometimes the use of SP data is favourable to the use of RP data and vice versa. The authors believe there exists scope for future research which considers the development of new models that combine both types of data in a useful manner.

Machine learning models

As machine learning is an emerging technology, it is becoming a popular modelling technique. Rolnick et al. (2019) highlight its vast potential in the field of EVs, with applications ranging from vehicle-to-grid technology improvement to the development of EV batteries. Despite this potential, this SLR found that only one article used machine learning methods: Jia et al. (2020) used machine learning methods to build a prediction model of EV adoption. As such, there is scope for future research in this area to employ machine learning techniques to investigate different aspects of EV adoption.

6. Conclusion

The SLR presented in this article provides a summary of existing works on mathematical modelling of EV adoption, which will become more important moving forward in the transition to net zero. The scope of the review was defined in non ambiguous terms with the aim of answering specific research questions. All articles within this scope were considered by systematically searching relevant databases and curating them manually against the selection criteria.

The analysis revealed that the most frequently observed modelling technique is DCM, followed by ABM. As the lack of successful business models has been identified as a barrier to EV adoption, there is scope for future work here. Only one model employed machine learning methods, indicating that there is potential to integrate this emerging technology to improve existing research. However, this approach is accompanied by the need to use fair machine learning methods, to ensure that the models are unbiased and that a fair transition policy is output. For example, most existing models do not make the distinction between urban and rural areas, meaning that those in rural areas may be disadvantaged as the more general models fail to acknowledge the extra constraints in the transition to EVs in these areas.

To further reduce model bias, it may be useful to parameterise future models using RP datasets, which are based on actual behaviour. Most existing models are parameterised by SP datasets, which are based on predictions of behaviour and may not align with actual behaviour. However, the bias introduced by the use of RP datasets when modelling future EV adoption must be considered, as discussed in Section 5.

Despite the fact that mathematical modelling has made a useful contribution to the successful transition to EVs, there still exist a number of challenges which must be overcome in order to maximise the impact of this tool. As each model must be parameterised, there is a need for data and particularly data relating to travel behaviour. Travel behaviour data is considered sensitive and private information, so it may be difficult to obtain reliable data of this type.

Furthermore, any intervention proposed through the use of mathematical modelling has the potential to introduce secondary consequences. For example, the increased risk to pedestrian safety discussed in Section 5 is a secondary consequence of increased EV usage. Given that most countries are only just beginning a transition to EVs, there are potentially many other secondary consequences which have not yet been considered or observed. For this reason, it is important that the variables considered in mathematical models of EV adoption are carefully chosen and constructed. Towards this goal, it is important to consult as many stakeholders as possible when constructing models. Additionally, it must be observed that no mathematical model is entirely representative of the real world, and that they are merely a useful guidance tool in optimising the transition. Therefore it is important that sensitivity analysis is performed to ensure robustness of modelling results in the presence of uncertainty.

Whilst existing works make important suggestions regarding certain aspects of the problem of transitioning to EVs, the majority of models focused solely on investigating the factors influencing EV adoption and predicting EV adoption, and it may be advantageous to model multiple aspects of the problem together in order to observe how they interact and affect each other. As discussed in Section 5, there are a number of aspects to model, as there are a number of barriers to EV adoption that must be considered. In other words, there is a need for a 'whole system approach'. The whole system approach refers to incorporating multiple models and approaches to solve the problem of how to facilitate EV adoption as a whole. For example, to achieve optimal EV adoption, the energy mix used to charge EV batteries must be considered, along with what will happen to the batteries after they expire.

CRediT authorship contribution statement

Lucy Maybury: Conceptualisation, Data curation, Formal analysis, Investigation, Methodology, Resources, Writing – original draft, Writing – review & editing. **Padraig Corcoran:** Conceptualisation, Funding acquisition, Investigation, Project administration, Resources, Software, Supervision, Validation, Visualisation, Writing – review & editing. **Liana Cipcigan:** Conceptualisation, Funding acquisition, Resources, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data access statement

All data is provided in full in the results section of this paper.

Acknowledgements

This study is partially funded by an EPSRC DTP Ph.D. studentship. It is also partially funded by an EPSRC, United Kingdom grant for Decarbonising Transport through Electrification, A Whole System Approach (DTE) grant number EP/S032053/1. The authors would like to thank Dr. Andrei Gagarin for supporting the process of selecting articles for review, and Prof. Irena Spasić for the guidance on conducting SLRs.

References

Ahuja, J., Dawson, L., Lee, R., 2020. A circular economy for electric vehicle batteries: driving the change. J. Prop. Plan. Environ. Law.
Al-Tayari, A.M., Chen, S., Sun, Z., 2020. A coupled torsional-transition nonlinear vibration and dynamic model of a two-stage helical gearbox reducer for electric vehicles. Shock Vib. 2020.
Alamerew, Y.A., Brissaud, D., 2020. Modelling reverse supply chain through system dynamics for realizing the transition towards the circular economy: A case study on electric vehicle batteries. J. Cleaner Prod. 254, 120025.
Austmann, L.M., 2020. Drivers of the electric vehicle market: A systematic literature review of empirical studies. Finance Res. Lett. 101846.
Barter, G.E., Tamor, M.A., Manley, D.K., West, T.H., 2015. Implications of modeling range and infrastructure barriers to adoption of battery electric vehicles. Transp. Res. Rec. 2502 (1), 80–88.
Bibak, B., Tekiner-Moğulkoç, H., 2021. A comprehensive analysis of Vehicle to Grid (V2G) systems and scholarly literature on the application of such systems. Renew. Energy Focus 36, 1–20.
Bitencourt, L., Abud, T., Santos, R., Borba, B., 2021. Bass diffusion model adaptation considering public policies to improve electric vehicle sales—A Brazilian case study. Energies 14 (17), 5435.
Brand, C., Cluzel, C., Anable, J., 2017. Modeling the uptake of plug-in vehicles in a heterogeneous car market using a consumer segmentation approach. Transp. Res. A 97, 121–136.
Brozynski, M.T., Leibowicz, B.D., 2020. Markov models of policy support for technology transitions. European J. Oper. Res. 286 (3), 1052–1069.
Cen, X., Lo, H.K., Li, L., Lee, E., 2018. Modeling electric vehicles adoption for urban commute trips. Transp. Res. B 117, 431–454.
Cho, Y., Blommestein, K.V., 2015. Investigating the adoption of electric vehicles using agent-based model. In: 2015 Portland International Conference on Management of Engineering and Technology. PICMET, IEEE, pp. 2337–2345.
Coffman, M., Bernstein, P., Wee, S., 2015. Factors affecting EV adoption: A literature review and EV forecast for hawaii. Electr. Veh. Transp. Cent. 1–36.
Coffman, M., Bernstein, P., Wee, S., 2017. Electric vehicles revisited: A review of factors that affect adoption. Transp. Rev. 37 (1), 79–93.
Danielis, R., Giansoldati, M., Rotaris, L., 2018. A probabilistic total cost of ownership model to evaluate the current and future prospects of electric cars uptake in Italy. Energy Policy 119, 268–281.
de Corte, K., Cairns, J., Grieve, R., 2021. Stated versus revealed preferences: An approach to reduce bias. Health Econ. 30 (5), 1095–1123.
de Luca, S., Di Pace, R., Marano, V., 2015. Modelling the adoption intention and installation choice of an automotive after-market mild-solar-hybridization kit. Transp. Res. C 56, 426–445.
de Rubens, G.Z., Noel, L., Kester, J., Sovacool, B.K., 2020. The market case for electric mobility: Investigating electric vehicle business models for mass adoption. Energy 194, 116841.
Department for Business, Energy & Industrial Strategy, 2020. 2019 UK greenhouse gas emissions, provisional figures. https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/875485/2019_UK_greenhouse_gas_emissions_provisional_figures_statistical_release.pdf. (Accessed: 30 April 2021).
Department for Environment, Food and Rural Affairs, 2020. Rural population and migration 2020. https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/912408/Rural_population__August_2020.pdf. (Accessed 19 July 2021).
Department for Transport, 2017. National Travel Survey: England 2017. https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/729521/national-travel-survey-2017.pdf. (Accessed 15 July 2021).
Dong, Y., 2018. Electric vehicle charging station quantity forecasting model. In: AIP Conference Proceedings, Vol. 1971, no. 1. AIP Publishing LLC, 040020.
Eggers, F., Eggers, F., 2011. Where have all the flowers gone? Forecasting green trends in the automobile industry with a choice-based conjoint adoption model. Technol. Forecast. Soc. Change 78 (1), 51–62.
Feng, B., Ye, Q., Collins, B.J., 2019. A dynamic model of electric vehicle adoption: The role of social commerce in new transportation. Inf. Manag. 56 (2), 196–212.
Gagniuc, P.A., 2017. Markov Chains: from Theory to Implementation and Experimentation. Wiley.
Geels, F.W., 2002. Technological transitions as evolutionary reconfiguration processes: A multi-level perspective and a case-study. Res. Policy 31 (8–9), 1257–1274.
Geels, F.W., 2012. A socio-technical analysis of low-carbon transitions: introducing the multi-level perspective into transport studies. J. Transp. Geogr. 24, 471–482.
Guo, L., Li, G., Gao, B., Chen, H., 2014. Shift schedule optimization of 2-speed electric vehicle using model predictive control. In: Proceedings of the 33rd Chinese Control Conference. IEEE, pp. 156–161.
Harbo, S.F., Zaferanlouei, S., Korpås, M., 2018. Agent based modelling and simulation of plug-in electric vehicles adoption in norway. In: 2018 Power Systems Computation Conference. PSCC, IEEE, pp. 1–7.
Hardman, S., 2019. Understanding the impact of reoccurring and non-financial incentives on plug-in electric vehicle adoption–A review. Transp. Res. A 119, 1–14.
Hardman, S., Chandan, A., Tal, G., Turrentine, T., 2017. The effectiveness of financial purchase incentives for battery electric vehicles–A review of the evidence. Renew. Sustain. Energy Rev. 80, 1100–1111.
He, L., Wang, M., Chen, W., Conzelmann, G., 2014. Incorporating social impact on new product adoption in choice modeling: A case study in green vehicles. Transp. Res. D 32, 421–434.

Higgins, A., Paevere, P., Gardner, J., Quezada, G., 2012. Combining choice modelling and multi-criteria analysis for technology diffusion: An application to the uptake of electric vehicles. Technol. Forecast. Soc. Change 79 (8), 1399–1412.

HM Government, 2021a. Industrial decarbonisation strategy. https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/970229/Industrial_Decarbonisation_Strategy_March_2021.pdf. (Accessed 29 April 2021).

HM Government, 2021b. The road to zero. https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/739460/road-to-zero.pdf. (Accessed 5 May 2021).

HM Government, 2021c. Zero emission vehicles. https://publications.parliament.uk/pa/cm5802/cmselect/cmtrans/27/2702.htm. (Accessed: 10 august 2021).

Huang, S., Srinivasan, R., Pekny, J.F., Reklaitis, G.V., 2012. Agent-based simulation framework for public bus fleet electrification investment analysis. In: Computer Aided Chemical Engineering, Vol. 31. Elsevier, pp. 1226–1230.

Huimin, L., Tengyu, G., 2011. Model to forecast the popularity of electric vehicles. In: 2011 Second International Conference on Mechanic Automation and Control Engineering. IEEE, pp. 417–421.

Javid, R.J., Nejat, A., 2017. A comprehensive model of regional electric vehicle adoption and penetration. Transp. Policy 54, 30–42.

Jia, W., Jiang, Z., Chen, T.D., Paleti, R., 2019. Evaluating fuel tax revenue impacts of electric vehicle adoption in virginia counties: Application of a bivariate linear mixed count model. In: International Conference on Transportation and Development 2019: Innovation and Sustainability in Smart Mobility and Smart Cities. American Society of Civil Engineers Reston, VA, pp. 91–110.

Jia, J., Shi, B., Che, F., Zhang, H., 2020. Predicting the regional adoption of electric vehicle (EV) with comprehensive models. IEEE Access 8, 147275–147285.

Jin, F., Yao, E., An, K., 2020. Understanding customers' battery electric vehicle sharing adoption based on hybrid choice model. J. Cleaner Prod. 258, 120764.

Karaaslan, E., Noori, M., Lee, J., Wang, L., Tatari, O., Abdel-Aty, M., 2018. Modeling the effect of electric vehicle adoption on pedestrian traffic safety: An agent-based approach. Transp. Res. C 93, 198–210.

Kaur, N., Sahdev, S.L., Bhutani, R.S., 2021. Analyzing adoption of electric vehicles in India for sustainable growth through application of technology acceptance model. In: 2021 International Conference on Innovative Practices in Technology and Management. ICIPTM, IEEE, pp. 255–260.

Khan, S., Maoh, H., 2015. A framework for collecting stated preference data on electric vehicle (EV) adoption by the Canadian fleet operators. In: Canadian Transportation Research Forum 50th Annual Conference-Another 50 Years: Where to from Here?//un Autre 50 Ans: Qu'en Est-Il À Partir De Maintenant? Montreal, Quebec, May 24-26, 2015.

Khan, S., Maoh, H., Dimatulac, T., 2021. The demand for electrification in Canadian fleets: A latent class modeling approach. Transp. Res. D 90, 102653.

Khazaei, H., 2019. The datasets of factors influencing adoption of electric cars in Malaysia: A structural equation modelling (SEM) analysis. Data Brief 27, 104644.

Kim, Y.-T., Choi, S.-W., 2019. A study on predicted expansion of electric vehicles using the technology adoption life cycle model: Focusing on the US market.

Kitchenham, B., 2004. Procedures for performing systematic reviews. Keele, UK, Keele University 33 (2004), 1–26.

Köhler, J., Turnheim, B., Hodson, M., 2020. Low carbon transitions pathways in mobility: Applying the MLP in a combined case study and simulation bridging analysis of passenger transport in the netherlands. Technol. Forecast. Soc. Change 151, 119314.

Köhler, J., Whitmarsh, L., Nykvist, B., Schilperoord, M., Bergman, N., Haxeltine, A., 2009. A transitions model for sustainable mobility. Ecol. Econom. 68 (12), 2985–2995.

Kumar, R.R., Alok, K., 2020. Adoption of electric vehicle: A literature review and prospects for sustainability. J. Cleaner Prod. 253, 119911.

Li, J., Jiao, J., Tang, Y., 2020. Analysis of the impact of policies intervention on electric vehicles adoption considering information transmission—based on consumer network model. Energy Policy 144, 111560.

Liao, F., Molin, E., Timmermans, H., van Wee, B., 2018. The impact of business models on electric vehicle adoption: A latent transition analysis approach. Transp. Res. A 116, 531–546.

Liao, F., Molin, E., Timmermans, H., van Wee, B., 2019. Consumer preferences for business models in electric vehicle adoption. Transp. Policy 73, 12–24.

Liao, F., Molin, E., van Wee, B., 2017. Consumer preferences for electric vehicles: A literature review. Transp. Rev. 37 (3), 252–275.

Liu, Y., Cirillo, C., 2017. A generalized dynamic discrete choice model for green vehicle adoption. Transp. Res. Proc. 23, 868–886.

Liu, Y., Ouyang, Z., Cheng, P., 2019. Predicting consumers' adoption of electric vehicles during the city smog crisis: An application of the protective action decision model. J. Environ. Psychol. 64, 30–38.

LTA, 2004. Singapore Land Transport Statistics in Brief 2004. Land Transport Authority of Singapore Singapore.

Massiani, J., Gohs, A., 2015. The choice of bass model coefficients to forecast diffusion for innovative products: An empirical investigation for new automotive technologies. Res. Transp. Econ. 50, 17–28.

Moore, D., Currano, R., Sirkin, D., 2020. Sound decisions: How synthetic motor sounds improve autonomous vehicle-pedestrian interactions. In: 12th International Conference on Automotive User Interfaces and Interactive Vehicular Applications. pp. 94–103.

Mulholland, E., Tattini, J., Ramea, K., Yang, C., Gallachóir, B.P.O., 2018. The cost of electrifying private transport–Evidence from an empirical consumer choice model of Ireland and Denmark. Transp. Res. D 62, 584–603.

Murphy, J.J., Allen, P.G., Stevens, T.H., Weatherhead, D., 2005. A meta-analysis of hypothetical bias in stated preference valuation. Environ. Resour. Econ. 30 (3), 313–325.

Nazari, F., Mohammadian, A.K., Stephens, T., 2019. Modeling electric vehicle adoption considering a latent travel pattern construct and charging infrastructure. Transp. Res. D 72, 65–82.

Nian, V., Hari, M., Yuan, J., 2019. A new business model for encouraging the adoption of electric vehicles in the absence of policy support. Appl. Energy 235, 1106–1117.

Pasaoglu, G., Harrison, G., Jones, L., Hill, A., Beaudet, A., Thiel, C., 2016. A system dynamics based market agent model simulating future powertrain technology transition: Scenarios in the EU light duty vehicle road transport sector. Technol. Forecast. Soc. Change 104, 133–146.

Pettifor, H., Wilson, C., McCollum, D., Edelenbosch, O.Y., 2017. Modelling social influence and cultural variation in global low-carbon vehicle transitions. Global Environ. Change 47, 76–87.

Prakash, S., Dwivedy, M., Poudel, S.S., Shrestha, D.R., 2018. Modelling the barriers for mass adoption of electric vehicles in Indian automotive sector: An interpretive structural modeling (ISM) approach. In: 2018 5th International Conference on Industrial Engineering and Applications. ICIEA, IEEE, pp. 458–462.

Rolnick, D., Donti, P.L., Kaack, L.H., Kochanski, K., Lacoste, A., Sankaran, K., Ross, A.S., Milojevic-Dupont, N., Jaques, N., Waldman-Brown, A., et al., 2019. Tackling climate change with machine learning. arXiv preprint arXiv:1906.05433.

Ruan, P., Wu, G., Wei, Z., Barth, M.J., 2021. A modularized electric vehicle model-in-the-loop simulation for transportation electrification modeling and analysis. In: 2021 IEEE International Intelligent Transportation Systems Conference. ITSC, IEEE, pp. 1685–1690.

Shafiei, E., Davidsdottir, B., Leaver, J., Stefansson, H., Asgeirsson, E.I., 2017. Energy, economic, and mitigation cost implications of transition toward a carbon-neutral transport sector: A simulation-based comparison between hydrogen and electricity. J. Cleaner Prod. 141, 237–247.

Shankar, A., Kumari, P., 2019. Exploring the enablers and inhibitors of electric vehicle adoption intention from sellers' perspective in India: A view of the dual-factor model. Int. J. Nonprofit Volunt. Sect. Mark. 24 (4), e1662.

Silvia, C., Krause, R.M., 2016. Assessing the impact of policy interventions on the adoption of plug-in electric vehicles: An agent-based model. Energy Policy 96, 105–118.

Smith, B., Olaru, D., Jabeen, F., Greaves, S., 2017. Electric vehicles adoption: Environmental enthusiast bias in discrete choice models. Transp. Res. D 51, 290–303.

Soltani-Sobh, A., Heaslip, K., Bosworth, R., Barnes, R., Yook, D., 2016. An aggregated panel data analysis to model electric vehicle adoption rates. Technical Report.

Tal, G., Xing, Y., Wang, Y., Sun, S., 2018. Motivations and barriers associated with the adoption of battery electric vehicles in Beijing: A multinomial logit model approach.

Tian, X., Su, H., Wang, F., Zhang, K., Zheng, Q., 2019. A electric vehicle charging station optimization model based on fully electrified forecasting method. Eng. Lett. 27 (4).

Tiwari, V., Aditjandra, P., Dissanayake, D., 2020. Public attitudes towards electric vehicle adoption using structural equation modelling. Transp. Res. Proc. 48, 1615–1634.

United Nations, 2016. The Paris agreement. https://unfccc.int/sites/default/files/resource/parisagreement_publication.pdf. (Accessed 16 February 2022).

US Bureau of Labor Statistics, 2022. Consumer price INDEX – January 2022. https://www.bls.gov/cpi/news.htm. (Accessed 18 February 2021).

Venkatesh, V., Morris, M.G., Davis, G.B., Davis, F.D., 2003. User acceptance of information technology: Toward a unified view. MIS Q. 425–478.

Vilchez, J.J.G., Jochem, P., 2019. Simulating vehicle fleet composition: A review of system dynamics models. Renew. Sustain. Energy Rev. 115, 109367.

Weidt, F., Silva, R., 2016. Systematic literature review in computer science-a practical guide. Relatórios Técnicos Do DCC/UFJF 1.

Welsh Government, 2021. Electric vehicle charging strategy for Wales. https://gov.wales/sites/default/files/publications/2021-03/electric-vehicle-charging-strategy-wales.pdf. (Accessed 07 February 2022).

Wesseling, J.H., Bidmon, C., Bohnsack, R., 2020. Business model design spaces in socio-technical transitions: The case of electric driving in the Netherlands. Technol. Forecast. Soc. Change 154, 119950.

WHO, 2018. SDG INdicator 11.6.2 concentrations of fine particulate matter (PM2.5). https://www.who.int/data/gho/data/indicators/indicator-details/GHO/concentrations-of-fine-particulate-matter-(pm2-5). (Accessed: 11 August 2021).

Yao, J., Xiong, S., Ma, X., 2020. Comparative analysis of national policies for electric vehicle uptake using econometric models. Energies 13 (14), 3604.

Yoon, T., Cherry, C.R., Ryerson, M.S., Bell, J.E., 2019. Carsharing demand estimation and fleet simulation with EV adoption. J. Cleaner Prod. 206, 1051–1058.

Zhou, Y., Levin, T., Plotkin, S.E., 2016. Plug-In Electric Vehicle Policy Effectiveness: literature Review. Argonne National Lab.(ANL), Argonne, IL (United States).

Zhuge, C., Wei, B., Shao, C., Dong, C., Meng, M., Zhang, J., 2020. The potential influence of cost-related factors on the adoption of electric vehicle: An integrated micro-simulation approach. J. Cleaner Prod. 250, 119479.