

A comprehensive review of integrating behavioral drivers of technology adoption and energy service use in energy system models

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ARTICLE INFO

Keywords:

Energy system modelling
Energy service use
Energy consumption
Technology adoption
Social science
Behavioral drivers

ABSTRACT

Energy System Models (ESMs) that aim at describing and exploring pathways towards a decarbonized future energy system currently account insufficiently for the behavior of households and individuals. To address this shortcoming, this study evaluates models' existing approaches to incorporate behavior considering social science insights to advance the models' behavioral realism. A structured literature review and expert interviews were employed, selecting sixteen ESMs and two sectoral energy models for further investigation. Main data sources for the analysis were model descriptions and interview notes. The results show a predominant focus of models on financial aspects of adoption decisions and energy service use, while there is less consideration of non-economic behavioral drivers. Models also often rely on a weak empirical foundation for behavioral drivers. Based on these findings, advancing the representation of behavior in ESMs is needed to strengthen the realism of models' explorative and descriptive insights. This analysis outlines concrete strategies to guide such an endeavor. It is recommended to consider relevant drivers of energy-related behavior, to employ a data-driven approach which relates behavioral outcomes to these drivers, and to define actor heterogeneity according to meaningful behavioral differences. In comparison to optimization approaches, the flexibility of simulation modelling provides a wider range of options for incorporating and analyzing behavioral aspects in ESMs. Future interdisciplinary research should further align social science insights with energy system modelling, building on the suggested strategies, to improve the accuracy of model predictions and to facilitate the consideration of behavioral aspects in the energy transition.

1. Introduction

Global surface temperature has been rising over the past decades as a result of human activities [1]. According to the Intergovernmental Panel on Climate Change [1], the fast and profound reduction of anthropogenic greenhouse gas emissions necessitates a transition towards renewable energy sources. Energy System Models (ESMs) have become indispensable tools in the planning of this transition [2,3]. Depending on a model's structure and purpose, ESMs can offer normative and prescriptive insights into future states of the energy system or describe and explore potential future decarbonization strategies and transition pathways [4,5].

To bring about the transition towards a decarbonized energy system, the importance of both technological advances as well as human behavior changes has been emphasized [6–8]. Such findings highlight

the necessity to consider relevant technological developments as well as behavioral dynamics in ESMs to comprehensively explore and describe pathways to achieve an energy transition [9,10]. Encouraging the incorporation of behavior in ESMs simultaneously raises attention regarding the social side of the energy transition, and fosters an increased consideration of potential distributional impacts and energy justice issues [10,11]. In spite of these benefits, existing ESMs that aim at describing and exploring possible transition pathways usually capture substantial technological detail, while considering human behavior to a limited extent [2,4]. In fact, only few ESMs include non-optimizing behavioral strategies beyond cost minimization or utility maximization [12].

Recent years have seen an increase in publications on the topic of behavior in ESMs. Previous review studies do raise attention regarding social aspects of energy system modelling, but are usually restricted to a sub-set of models and technologies [2,3] or describe generalized

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<https://doi.org/10.1016/j.rser.2025.115520>

Received 13 June 2024; Received in revised form 24 December 2024; Accepted 17 February 2025

Available online 26 February 2025

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Abbreviations:	
ABM	Agent-based modelling
ESM	Energy System Model
TPB	Theory of Planned Behavior
VBN	Value-Belief-Norm Theory

approaches for modelling behavior [9,13,14]. This work builds on prior studies in explicitly addressing how social science findings regarding human behavior can be aligned with concrete behavioral modelling strategies. To the best of the authors’ knowledge, it is thereby the first investigation to exemplify how social science insights can be combined with energy modelling, arriving at concrete guidelines to advance models’ behavioral realism.

This study first provides further background information on energy-related behavior and energy system modelling. Then, a structured review regarding the incorporation of behavioral aspects of households and individuals in ESMs is provided. Last, insights are synthesized to arrive at a concrete and feasible research agenda for advancing the knowledge base at the interface of social science and energy system modelling.

2. Energy-related behavior and its drivers

Among the range of actors involved in the energy transition, the behavior of households and individuals often does not follow readily predictive and cost-optimizing patterns [15]. To elucidate their behavioral patterns, previous research has investigated a multitude of predictors of both pro-environmental behavior and, more specifically, energy-related behavior. Energy-related behaviors are defined as behaviors which directly result in end-use energy demand, namely, the adoption of energy-related technologies and the use of those technologies (i.e. energy service use) [7]. This study also includes the adoption of rooftop solar, albeit officially regarded a supply technology. The main focus of this analysis is on behavior in the residential and transport sector, as consumer behavior directly impacts emissions in these two areas [16]. The following section summarizes insights of reviews and meta-analyses to provide an overview of main empirically studied drivers of energy-related behavior according to the six categories shown in Table 1.

2.1. Pro-environmental drivers

Various pro-environmental drivers of energy-related behavior have been investigated. Research has distinguished different types of values (e.g. biospheric, altruistic, hedonic, egoistic). Biospheric values, emphasizing the intrinsic worth of the environment, tend to be most closely correlated with pro-environmental behavior [17]. Lanzini et al. [18] and Carrus et al. [19], however, report mixed findings regarding the impact of environmental values on behavior. This ambiguity may be explained by contextual aspects acting as barriers (e.g. lack of infrastructure), inhibiting the impact of values on pro-environmental actions [20].

Beyond peoples’ underlying values, studies confirm the predictive qualities of more concrete cognitions, such as pro-environmental attitudes, beliefs, (personal) norms, perceived behavioral control (i.e. beliefs regarding one’s ability to execute a behavior), and behavioral intentions [15,18,19,21–27]. Research indicates that, in some cases, behavioral intentions mediate the relationship between underlying behavioral drivers and behavioral outcomes [26,28]. Pro-environmental knowledge and education have also been identified as drivers of energy-related behavior [21,22,24,28]. Steg et al. [15] note that pro-environmental knowledge alone does not fully explain behavior. For

Table 1
Drivers of energy-related behavior.

Category	Drivers	Examples of related theories
Pro-environmental drivers	• Values • Attitudes • Beliefs • (Personal) norms • Behavioral intentions • Perceived behavioral control • Pro-environmental knowledge and education	• Theory of Planned Behavior (TPB) • Reasoned Action Approach • Norm Activation Model • Value Belief Norm Theory (VBN)
Appraisal of technologies and energy services	• Perceptions of (characteristics of) technologies • Cost perceptions • Well-being perceptions (comfort, safety, etc.) • Emotions	• Technology Acceptance Model • Rogers’ Theory of Innovation Adoption • Bounded Rationality Theory
Familiarity	• (Past) experience(s) • Habits • Lifestyle	• Prospect Theory • Habit Discontinuity Hypothesis • Self-Regulated Behavioral Change Model
Socio-demographic drivers	• Economic status • Age • Education • Gender • Dwelling ownership status • Other (e.g. marital status, household size, employment)	
Social drivers	• Social norms • (Direct) social interactions	• Social Network Theories • TPB • VBN • Social Practice Theory
Contextual drivers	• Dwelling characteristics • Environmental conditions (e.g. urban heat island effect) • Infrastructure/spatial aspects • Other (e.g. car availability)	

Note. A description of the mentioned theories is provided in Appendix C.

instance, individuals might possess adequate pro-environmental knowledge, but may yet misjudge the impact of their personal behavior on the environment.

The Theory of Planned Behavior (TPB) and its successor, the Reasoned Action Approach, provide a framework on which various of the previously mentioned pro-environmental drivers are based [29,30]. The theories posit beliefs, existing (social and personal) norms, and individuals’ perceived behavioral control to result in intentions, which in turn determine behavior. Due to a so-called “intention-behavior gap”, however, behavioral intentions may not always lead to actual behavior [18,31]. The Norm Activation Model is also frequently mentioned in the literature, explaining behavior by personal norms which are activated through awareness and feelings of responsibility [32]. The theory’s extension, the Value Belief Norm (VBN) theory, accounts for behavior through different values (egoistic, biospheric, altruistic) that impact beliefs which influence personal norms [33].

2.2. Appraisal of technologies and energy services

Individuals’ and households’ perceptions of technologies and energy services can impact behavior. Research has highlighted the appraisal of technologies’ costs, performance, quality, and benefits as drivers of energy-related behavior [21,24,34]. Studies also indicate affective appraisals to influence energy-related behaviors [19]. For instance,

feelings of excitement and enjoyment towards technologies can impact technology choices [34,35].

The Technology Acceptance Model incorporates technologies' perceived usefulness and ease of use as main contributors to adoption decisions [24,36]. These aspects are expanded by Rogers' theory of innovation adoption, listing various characteristics of technologies that influence the perceptions of potential buyers, such as technologies' visibility, complexity, and relative advantage (i.e., relative cost savings compared to other technologies) [37]. Adoption decisions are also addressed by the concept of bounded rationality, which was proposed to explain non-optimal decisions making from a financial perspective [38]. The concept is integrated in the Cumulative Prospect Theory, describing that when decision making involves risks, people tend to strive for minimizing potential losses [39].

Studies on the appraisal of energy services indicate the level of energy prices to impact behavior [40,41]. A meta-analysis by Labandeira [42] reports that behavioral changes in response to energy prices tend to occur gradually, leading to stronger reactions to energy prices in the long-term (i.e. over several years) compared to the short-term (i.e. over a period of one year). Gasoline consumption appears to be most sensitive to price changes, while heating oil consumption was found to be the least impacted by price changes. Research also suggests that people might increase their use of energy services after the implementation of measures to save energy or use renewable energy [43]. As a result of such rebound effects, expected energy savings may be lowered or even offset [44].

2.3. Familiarity

Past or current behaviors can impact future behaviors through preferences, habits, and lifestyles [18,21,26,35,45,46]. Thereby, preferences may be more related to adoption decisions, and habitual behavior tends to impact the use of energy services more [7]. It should be noted that preferences and habits can change over time. The habit discontinuity hypothesis states that such modifications are most likely to occur in conjunction with contextual changes, such as renovation measures [47]. Habit changes usually also require individuals to be motivated to change (see Self-Regulated Behavioral Change Model [48]). Regarding lifestyles, Chadwick et al. [21] argue that peoples' broader personal aims, such as striving for independence, influence energy-related behaviors. Nevertheless, only few studies to date have investigated energy-related lifestyles, resulting in scarce knowledge regarding the exact manners in which the notion relates to energy-related behavior [49].

2.4. Socio-demographic drivers

For this study, socio-demographic drivers are defined as social and demographic characteristics of individuals and households which exert a (direct or indirect) impact on their energy-related behavior. Economic aspects, in particular, have received substantial attention in research. For example, lower income has been associated with relatively lower adoption of technologies [22,50]. Low income and being affected by energy poverty has also been found to correlate with the under-consumption of energy [51,52]. The overall importance of economic aspects driving energy-related behavior is subject to mixed findings [22]. Diverging results of studies may partially be explained by people showing different behaviors depending on the sector, the type of fuel consumption, and the type of transport mode [22,53–55]. For instance, Oswald et al. [55] found the consumption of heat and electricity to be relatively less affected by income compared to transport behavior.

Other socio-demographic drivers that have frequently been assessed in the context of energy-related behavior consist of gender, age, education level, and (dwelling) ownership status [21,22,27,34,56–59]. For instance, elderly people and children tend to require or prefer higher indoor temperatures [56]. Regarding energy efficiency renovations,

homeowners usually have more control and larger incentives compared to tenants [58]. Other socio-demographic drivers that have received some attention include, amongst others, marital status, household size, employment, and car availability [46,58,60]. Overall, findings regarding socio-demographic drivers are not always conclusive, suggesting that these drivers can partly elucidate energy-related behavior, but are alone insufficient to account for all variance in behavior [18,22,58].

Socio-demographic drivers can represent direct links with energy-related behavior, for instance, income directly determines the types of technologies one can afford. At the same time, socio-demographic aspects can also represent proxies for other underlying drivers of behavior. Education level, for instance, may relate to energy-related behavior through individuals' accumulated knowledge.

2.5. Social drivers

Individuals do not act in isolation, but shape and are shaped by their social surroundings. Perceived social norms serve to guide such social interactions [61]. Injunctive norms refer to individuals' beliefs regarding socially approved or disapproved behaviors and descriptive norms refer to the observed behaviors of others, which are perceived to be a norm [62]. Studies confirm the predictive value of social norms for energy-related behavior [21,25–28,54,63,64]. For instance, Bollinger and Gillingham [65] report a higher probability of Photovoltaic (PV) panel adoption when the number of installations in the same zip code area increases. The effect of the two types of norms and the overall strength of social influences on behavior may differ depending on the kind of energy-related behavior [66,67].

Regarding the conceptualization of social drivers, social network theories have frequently been mentioned, focusing on the impact of social relationships on behavior [34,63,68]. Social norms are also mentioned in the TPB [29] and VBN [33] as one of several drivers of behavior. Changes in social norms are captured by the notion of social tipping points, describing that small incremental modifications can result in self-reinforcing feedback mechanisms of transformation [69].

2.6. Contextual drivers

In this work, contextual drivers are defined as drivers related to either the transport or residential sector, which have a direct impact on energy-related behavior. Frequently studied contextual drivers encompass environmental conditions, the access to technologies, spatial aspects and infrastructure, building characteristics, car availability, and policy-related incentives [15,18,21,24,35,46,54,56]. For example, relatively cold outside temperatures have been shown to drive investments in heating technologies [56]. The urban heat island effect, characterized by higher temperatures in large cities compared to their surroundings [70], can also increase energy-related cooling demand while decreasing heating demand of urban areas. In the transport sector, infrastructure and spatial aspects can impact modal choices through their effects on travelling time and travelling distance [18,35,46]. Policy-related incentives, such as subsidies, have also been found to be predictors of energy-related behavior [24].

3. Energy system modelling

ESMs usually represent the demand and supply side of the energy system on various scales (e.g. regional, national, global) [71,72]. Models can be used as tools to either provide a normative and/or prescriptive (optimal) outlook of the future energy system or to describe and/or explore (realistic) transition pathways [4,5]. Most ESMs are optimization-based, calculating a desired future state of the energy system. Thus, models display the (theoretically) optimal energy mix at the system level for a given target, usually economic (i.e. minimizing total system costs), while often employing CO₂ reduction ambitions as a

constraining factor [9]. If behavioral aspects are included in optimization models, they tend to be based on a micro-economic foundation, assuming behavioral choices to be made with perfect foresight [2,9]. Optimization-based ESMs often follow normative or prescriptive purposes, elucidating possible future outcomes that can guide or steer a transition [5].

In contrast to optimization models, simulation ESMs calculate the evolution of the energy system without specifying a desired future state [11]. Thus, they usually follow a descriptive or explorative approach, aiming at investigating the system's development under assumed real-world conditions [9]. Rather than providing information on possible future outcomes, such models place more emphasis on the pathways and developments needed to reach a certain future state. Agent-Based Models (ABMs) can be considered a sub-category of ESMs following an overall simulation approach. For this work, simulation models are considered ABMs when they include different agents with individual behavioral rules, showing some form of interaction that leads to new patterns of emergent behavior [73]. Overall, more options to incorporate behavioral aspects exist in simulation ESMs, and especially ABMs have focused on defining realistic behavioral rules of heterogeneous agents and simulating social interaction patterns [9,74,75].

Trutnevyte et al. [13] differentiate three broad strategies for including social science findings in ESMs. First, bridging describes exchanges between modelling and social sciences insights. Second, an iterating strategy entails that social science findings directly inform models' input assumptions. Third, merging concerns the structural adaptation of existing models according to social science results. This analysis focuses on the merging strategy, as this approach allows for the most complete and balanced inclusion of human behavior in ESMs and provides a basis for examining societal transformation dynamics [13]. Following such strategy necessitates the simplification and quantification of complex social science insights, which is addressed in section 6.

4. Method

This research combined a structured literature search with expert interviews. The structured literature search served to retrieve relevant ESMs for review and the expert interviews helped to gain insights regarding overall benefits and challenges of incorporating behavior in ESMs. In the process of retrieving relevant models, the focus was on national ESMs. In contrast to aggregated global models, national ESMs can represent behavior in reasonable detail and contrary to sub-national and sectoral models, national ESMs capture the main components of the entire energy system. Sectoral energy models tend to be able to capture behavior at a higher level of detail compared to models encompassing the entire energy system, due to a narrower focus on only one economic sector. Thus, a few examples of such sectoral models were added to the review to ensure an elaborate illustration of the range of options for modelling behavior.

In the literature search, a structured database search was combined with a snowballing technique [76]. Scopus and Web of Science were used. Articles were included if they described or reviewed one or more ESM(s) that (1) incorporate behavioral aspects of households and/or individuals related to adoption decisions and/or energy service use in the residential and/or transport sector, and (2) model the entire energy system. The search terms are displayed in Table 2.

Fig. 1 displays an overview of the search process. After reviewing the papers' title and abstract and subsequently the full text, 20 papers were included. Some further models that were not retrieved by the literature search were selected based on consultations within the authors' networks. Eventually, sixteen ESMs and two sectoral models were selected. This number is smaller than the number of included papers, as multiple papers revolved around the same ESMs.

A set of comparison criteria was used to assess and contrast the methods by which models incorporated behavioral aspects (see Table 3). These criteria were created based on frequently studied drivers of

Table 2
Search strings used for structured database search.

Date of Search	Database	Search strings
October 2nd, 2023, and January 10th, 2024	Scopus	(TITLE-ABS-KEY (behav*) AND ALL (household* OR human* OR consumer* OR citizen* OR actor* OR person OR people) AND ALL ("energy system model*" OR "energy model*" OR esm) AND TITLE-ABS-KEY ("energy system*"))
	Web of Science	(behav* (All Fields)) and (household* OR human* OR consumer* OR citizen* OR actor* OR person OR people (All Fields)) and ("energy system model*" OR "energy model*" OR ESM (All Fields)) and ("energy system*" (All Fields))

Note. As Scopus covers a wider range of journals than Web of Science [77], it was necessary to limit the search terms in Scopus to title, abstract, and keywords to keep the number of results within a feasible range for review.

energy-related behavior (see section 2), the content of the ESMs, and the authors' own expertise and experience. The comparison criteria formed the basis for the review of ESMs.

Semi-structured interviews with six experts in the field served to gain further insights into benefits and challenges regarding the incorporation of behavior in ESMs. The experts' contacts were retrieved based on relevant scientific publications and the authors' networks. A semi-structured interview approach was chosen to allow for sufficient flexibility in the conversation while ensuring the main topics of interest to be covered [78]. Insights derived from the interviews are integrated in section 6. The interview questions as well as a summary of main findings can be found in Appendix A and Appendix B. In summary, the present analysis is based on model descriptions and documentations (retrieved by the structured literature search) as well as insights from expert interviews.

5. Review of ESMs

The following section gives an overview of the reviewed ESMs. The section then provides further detail regarding the inclusion of individual drivers of energy-related behavior identified in section 2 as well as general methodological considerations. Table 4 shows the selected models and their geographical focus.

Out of the sixteen ESMs chosen for this work, eleven models incorporate the behavior of households and individuals in both residential and transport sector. The remaining five models represent case studies which focus on either sector, with more models addressing the transport sector. Regarding behavioral outcomes, all models incorporate adoption decisions. Less attention is devoted to energy service use, with only half of the reviewed ESMs considering this aspect. In the models that do consider energy service use, the variable is often used as exogenous input. For example, the TIMES Households model derives transport demand data from a survey of individuals' transport behavior. Fig. 2 gives an overview of the review of ESMs according to the comparison criteria. Appendix D provides further detail regarding the inclusion of behavioral outcomes in each of the ESMs.

5.1. Drivers of behavior in ESMs

5.1.1. Pro-environmental drivers

The review identified only few ESMs that account for pro-environmental drivers of behavior. MUSE allows for incorporating various decision objectives of actors, amongst those environmental goals. As such, environmental decision objectives exert an impact on technologies' rankings that ultimately determine adoption decisions. A newer version of BLUE by Verrier et al. [45] accounts for pro-environmental values. The authors modify Rogers' [37] distribution of adopter attitudes to distinguish actors with various strengths of

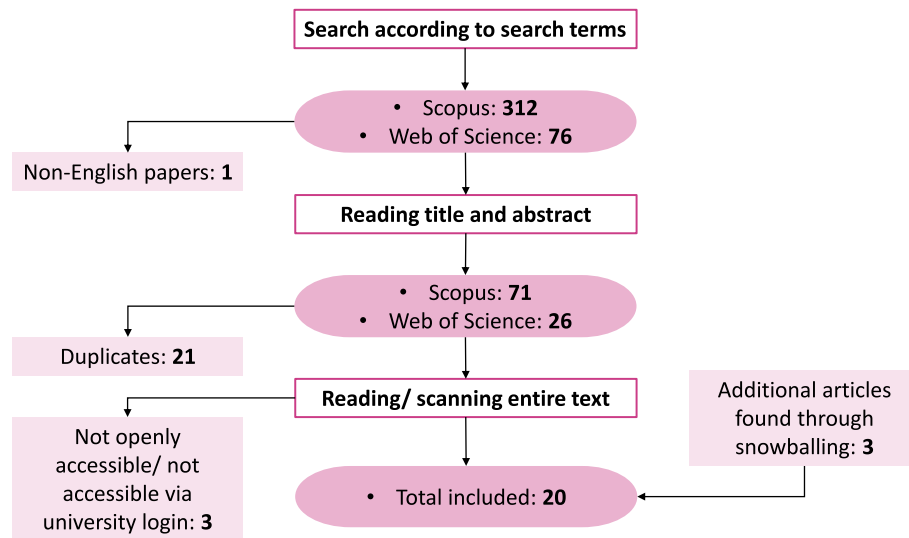


Fig. 1. Illustration of structured literature search.

Table 3

Comparison criteria for the selected ESMs.

Category	Criterion	Description
Behavior	Adoption decisions	Modelling of households' and/or individuals' adoption decisions regarding energy-related technologies
Drivers of behavior	Energy service use	Modelling of households' and/or individuals' energy use
	Pro-environmental	Drivers related to attitudes, values, perceptions, personal norms, and knowledge e.g. pro-environmental values, pro-environmental attitudes, pro-environmental knowledge
	Appraisal of technologies	Perceptions of technologies impacting energy-related behavior, e.g., technologies' complexity, emotions elicited by a technology, etc.
	Familiarity	Drivers related to existing or previous behavior of households and/or individuals, e.g. habits, lifestyle, (past) experiences
	Socio-demographic	Socio-demographic aspects influencing behavior, e.g. income, age, dwelling ownership status
Methodological aspects	Social	Inclusion of social drivers of behavior, e.g. interactions between actors, social norms
	Contextual	Incorporation of contextual drivers of behavior, e.g. (lack of) existing infrastructure
	Behavior changes	Modelling changes in the drivers of behavior over time, e.g. diffusion of pro-environmental values among the population
	Actor heterogeneity	Distinguishing actor heterogeneity to account for differences in the drivers of behavior among households and/or individuals
	Empirical basis	Considering empirical findings through informing drivers of behavior with empirical data or directly integrating empirical data into the model
	Modelling approach	Models are distinguished depending on: 1) their overall approach being optimization- or simulation-based 2) whether simulation models are considered ABMs

Table 4

Overview of selected models.

Model name	Geographical focus	Source(s)
TIMES Actor Model (TAM)	Germany	[79]
PRIMES	E.U.	[80]
CA-TIMES	California	[81]
TIMES Households model	France	[82]
MARKAL-MACRO	UK	[83]
IESA-sim	The Netherlands	[84]
ENSYSI	The Netherlands	[85]
MUSE	Global (case study: UK)	[86,87]
BLUE	UK	[45,88]
ENGAGE	U.S.	[89]
CIMS	Canada	[90]
UK TIMES	UK	[91]
ESME	UK	[92]
TIMES-IR & CA	Ireland & California	[93]
TIMES-DKEMS	Denmark	[94]
MoCho TIMES	Denmark	[95]
Sectoral energy models		
HESTIA	The Netherlands	[96]
ABMoS-DK	Denmark	[97]

pro-environmental values. Over time, actors are assumed to move towards the left of this distribution (i.e. developing stronger pro-environmental values), thereby increasing their adoption of low-carbon technologies. ENSYSI and IESA-sim determine the sustainability of technologies based on their CO₂ emissions. This score impacts technologies' overall ratings (which, in turn, determines adoption decisions), depending on the importance that an actor category is assumed to allocate to sustainability considerations.

5.1.2. Appraisal of technologies and energy services

Most reviewed ESMs account for behavioral aspects regarding financial considerations. Adoption decisions can then be determined through the costs of technologies (e.g. IESA-sim) or the Net Present Value of an investment (e.g. BLUE). In BLUE, PRIMES, ENSYSI, TAM, TIMES Households model, CIMS, UK MARKAL-MACRO, and CA-TIMES, specific discount rates (also called hurdle rates) are varied to "[give] initial investments (...) asymmetrically greater weight than future savings" [[80], p. 215]. For example, MARKAL-MACRO applies a higher discount rate for newer technologies to incorporate adoption barriers, such as individuals being hesitant to purchase or lacking information.

To deal with actors' differing sensitivity to costs, BLUE incorporates a "heterogeneity parameter" which accounts for changes in

Model	Behavior in sector(s)	Behavior	Drivers of Behavior					Methodological Aspects						
		Adoption decisions	Energy consumption	Pro-environmental	Appraisal of technologies	Familiarity	Socio-demographic	Social	Contextual	Actor Heterogeneity	Behavior Changes	Empirical basis	Approach	ABM
TIMES Actor Model (TAM)		✓	✗	✗	✓	✗	✗	✗	✗	–	✗	–	Optim.	–
PRIMES	 	✓	✓	✗	✓	✓	✓	✗	✓		✓	  	Optim.	–
CA-TIMES	 	✓	✗	✗	✓	✗	✗	✗	✗	–	✗	–	Optim.	–
TIMES Households model	 	✓	✓	✗	✓	✗	✓	✗	✓		✓	  	Optim.	–
MARKAL-MACRO	 	✓	✓	✗	✓	✗	✗	✗	✗	–	✗	  	Optim.	–
IESA-sim	 	✓	✗	✓	✓	✗	✗	✓	✗		✗	–	Simul.	ABM
ENSYSI	 	✓	✗	✓	✓	✗	✗	✓	✗		✗	–	Simul.	ABM
MUSE	 	✓	✗	✓	✓	✗	✓	✓	✓		✓	  	Simul.	ABM
BLUE	 	✓	✓	✓	✓	✓	✗	✓	✗		✓	  	Simul.	ABM
ENGAGE	 	✓	✗	✗	✓	✗	✓	✗	✗	–	✗	–	Simul.	No ABM
CIMS	 	✓	✓	✗	✓	✗	✗	✓	✗	–	✗	  	Simul.	No ABM
UK TIMES		✓	✗	✗	✓	✓	✓	✗	✗		✗	  	Optim.	–
ESME		✓	✓	✗	✓	✗	✗	✗	✓		✓	  	Optim.	–
TIMES-IR & CA		✓	✗	✗	✓	✗	✗	✗	✓	–	✓	  	Optim.	–
TIMES-DKEMS		✓	✓	✗	✓	✗	✗	✗	✓		✓	  	Optim.	–
MoCho TIMES		✓	✓	✗	✓	✗	✓	✗	✓		✓	  	Optim.	–
SECTORAL ENERGY MODELS														
HESTIA		✓	✓	✗	✗	✗	✓	✗	✓		✗	  	Simul.	ABM
ABMoS-DK		✓	✓	✗	✓	✓	✓	✓	✓		✓	  	Simul.	ABM

Fig. 2. Comparison of selected models.

Note: The symbols in the column “behavior in sector(s)” refer to the transport and residential sector. Red crosses signify “not included”, while green ticks stand for “included”. “Optim.” denotes optimization and “Sim.” refers to simulation. Actor heterogeneity is rated on a three-point scale: One stands for less than five actor groups, two signifies between five and twenty actor groups, and three denotes more than twenty actor groups. Models’ empirical basis is also rated on a three-point scale: One describes some behavioral data is used, two denotes that models have been empirically informed, and three means that models directly include empirical data.

technologies’ market share as a result of their cost-efficiency. Adjusting the parameter towards actors striving for perfect cost-optimization will therefore result in only the most cost-efficient technologies being adopted. Sensitivity to costs can also be accommodated probabilistically, including technologies with the highest Net Present Value the highest chance of being adopted (e.g. PRIMES).

Energy service use can be represented by the price elasticity of demand (BLUE, PRIMES, CIMS). This measure accounts for changes in energy demand as a result of changes in energy prices. MARKAL-MACRO addresses behavioral aspects of energy service use through demand-response behavior, assuming consumers to participate in demand-response for financial reasons.

In addition to financial motivations, ENSYSI and IESA-sim take into account actors’ preferences regarding technologies’ complexity, as described in Rogers’ theory [37]. Technologies receive a score depending on their complexity. The weighed sum of these scores is used to establish an overall ranking of technologies, with weights being determined depending on the significance that an actor category is assumed to assign to certain technology characteristics. In other models, non-financial aspects of technologies are monetized (i.e. intangible costs), such as representing transport modes’ speed in terms of a “cost of time” (PRIMES, ABMoS-DK, MoCho TIMES, CIMS). Overall, in the transport sector, models have characterized transport modes based on a multitude of dimensions (including time, speed, waiting time, congestion time, etc.), which can then be matched with users’ preferences regarding travelling time, distance, and trip purpose.

BLUE, CIMS and UK TIMES incorporate consumers’ direct preferences for certain technologies derived from empirical investigations. For instance, CIMS uses data from discrete choice surveys to estimate how much peoples’ likelihood of adopting a technology increases with a technology’s increasing market share. This aspect is implemented through decreasing intangible costs of technologies with increasing market share.

Individuals’ and households’ attitudes towards innovation are incorporated in ENSYSI, IESA-sim, and BLUE. The models use Rogers’ [37] theory to specify various actor groups with different propensities towards adopting innovative technologies. BLUE includes all five categories specified by Rogers, while IESA-sim and ENSYSI consider only four groups and deviate from the original theory in modifying the groups’ distances from the mean of the adoption distribution.

5.1.3. Familiarity

There are only a few ESMs that consider existing behavior increasing the likelihood of similar choices to be made in the future. In BLUE and UK TIMES, familiarity has been determined through empirical data regarding adoption preferences for future heating technologies. Based on these empirical findings, BLUE determines the rate of replacement of currently owned technologies when predicting technologies’ future market shares. UK-TIMES follows a slightly different approach, distinguishing household types based on empirical findings regarding preferences for heating technologies. According to the data, household types are assigned shares of newly installed technologies.

In the transport sector, existing mobility choices derived from surveys can be incorporated in the projection of future mobility demand (see TIMES-DKEMS, ABMoS-DK). For instance, when determining mobility choices, ABMoS-DK distinguishes agents based on existing car or bike ownership (derived from the Danish National Travel Survey) to establish actor heterogeneity. This aspect, in combination with other actor characteristics and trip characteristics, is used to assess future modal choices. ABMoS-DK also explicitly considers (habitual) travel behavior, since “in case that the derived utilities of alternative choices are equal, the agent continues to habitually repeat previous behaviour.” [97] p. 854].

5.1.4. Socio-demographic drivers

The most widely considered socio-demographic characteristic in

models is income (TIMES Households model, PRIMES, ENGAGE, MoCho TIMES, MUSE, ABMoS-DK). This focus corresponds with the tendency of existing research to investigate socio-demographic drivers related to financial capital (see section 2.4). Income can be modeled by using a higher discount rate for actors with lower financial budget, leading these actors to require higher rates of return from their investment (TIMES Household model). Alternatively, MoCho TIMES distinguishes households by income to assign differing intangible costs of transport modes depending on the respective income group.

Other socio-demographic drivers in ESMs include the number of bedrooms in a dwelling (UK TIMES), dwelling ownership status, and size of a household (TIMES Households model, PRIMES). For example, the TIMES Households model allows only building owners to make decisions regarding dwelling insulation. ABMoS-DK takes into account age, gender, and education level as attributes of agents, which determine their modal preferences.

A high level of detail regarding agents' socio-demographic characteristics is represented in MUSE. A case study by Sachs et al. [87] on the UK building sector describes the parametrization of agents based on a multitude of socio-demographic factors determined by the Sinus-Milieus model [98]. This distinction of agent categories in MUSE determines how agents search for new technologies and make adoption decisions.

5.1.5. Social drivers

Social drivers of energy service use were not addressed by any of the reviewed ESMs. Regarding adoption decisions, a total of five models account for social influences, mostly indirectly or through external assumptions. Mau et al. [90] model descriptive social norms indirectly through assuming that an increased market share of hybrid-electric vehicles further increases their likelihood of adoption in CIMS. ABMoS-DK incorporates social influence indirectly through overall developments in the transport sector. For instance, if all agents use cars, overall congestion time increases and future agents become less likely to choose cars.

Verrier et al. [45] model the diffusion of pro-environmental values across societal groups, assuming this diffusion to occur as a social process (BLUE). This mechanism is implemented through a "drift rate" that governs the speed by which actors' strength of pro-environmental values increases. IESA-sim and ENSYSI consider whether households perceive a technology as being evaluated by society as positive, neutral or negative. The weighed sum of this aspect and other technology characteristics (i.e. costs, CO₂ performance, complexity) is used to form a ranking of technologies that determines adoption. MUSE accounts for social influences through allowing some agents to transfer assets, thereby assuming certain patterns of interaction to occur between agents.

5.1.6. Contextual drivers

Contextual drivers of behavior tend to differ between the residential and transport sector. In the transport sector, individual transport choices can be modeled as being affected by cost, travel time and trip distance, which are matched with characteristics of transport modes to determine modal choices (ESME, TIMES-IR & CA). For transport modes that require fuel or electricity, PRIMES monetizes the available refueling or recharging infrastructure as part of the intangible costs of technologies. Regarding spatial aspects, ABMoS-DK and MoCho TIMES consider both residential region and urbanization type to account for differences in transport choices.

In the residential sector, households' housing characteristics are differentiated by the TIMES Household model, UK TIMES, HESTIA, and PRIMES. For instance, the TIMES Households model considers living area and dwellings' insulation quality when determining households' level of energy demand. HESTIA provides the most detailed account of contextual characteristics, considering each dwelling in the Netherlands according to a variety of characteristics (e.g. location, quality level, year of construction).

5.2. Methodological aspects

When including multiple drivers in a model, a key aspect regards how these drivers are combined into one behavioral outcome (i.e. an adoption decision or the level of energy service use). The reviewed ESMs deal with this aspect through establishing a weighed sum (IESA-sim), determining intangible costs (e.g. "costs of time" in PRIMES), or through defining the order of priority of decision objectives (MUSE) per actor group. Most detail is provided in MUSE, including six different options for combining agents' decision objectives (e.g. mean, weighed sum, lexical comparison). Few other methodological aspects arose from the review, which are described in the following sub-sections.

5.2.1. Behavior changes

Some of the ESMs display approaches to account for behavioral modifications over time. Energy consumption changes can be modeled as a decrease or increase in demand by a certain fixed factor in response to prices (see PRIMES and MARKAL-MACRO). Regarding adoption decisions, CIMS indirectly accounts for a change in decision preferences by assuming that with growing market shares of technologies, people will become increasingly more likely to adopt these technologies. Verrier et al. [45] include a parameter called "drift rate" in BLUE: If the rate reaches a pre-defined threshold, financial decisions objectives are out-weighed by peoples' preferences for a range of low-carbon technologies. BLUE also assumes that as the market share of technologies increases, people will move towards the left of the distribution of adopter attitudes and become more innovative.

Some of the ESMs include transport modal shifts, which represent a specific aspect of behavioral changes (TIMES Households model, PRIMES, TIMES-DKEMS, ESME, MoCho TIMES, TIMES-IR & CA). For instance, Daly et al. [93] account for changes in transport mode choices in two case studies using TIMES-IR and TIMES-CA. Overall travel demand and available travel time per capita are exogenous inputs, which are matched with transport modes' costs and travel times to determine modal choices. Pye and Daly [92] build on this approach, incorporating a maximum potential shift from car to non-car transport as well as an annual rate of shift per transport mode into ESME.

5.2.2. Actor heterogeneity

The incorporation of different actor groups allows for an explicit account of behavioral variations, meaning that per actor group, specific patterns of behavior (e.g. decision objectives) must be defined. The models CIMS, TIMES-IR & CA, and MARKAL-MACRO assume one centralized actor and do not consider behavioral differences. Most other reviewed models establish two to five actor groups. For example, ENSYSI, IESA-sim, and BLUE distinguish individuals by four to five adopter attitudes, which differ in the weight they assign to a number of adoption decision objectives. PRIMES and MoCho TIMES differentiate four to five income groups, with intangible costs or discount rates differing per group. UK TIMES categorizes three households types depending on the number of bedrooms. Each household type is assumed to follow a different adoption pattern. In the transport sector, heterogeneity can be created by dividing individuals based on trip length, trip region and available travel time, which determines preferred mode(s) of transport (see ESME).

A more detailed approach to incorporating behavioral heterogeneity is exemplified by the TIMES Households model, where 180 household groups in the residential sector and 120 household groups in the transport sector are created based on various socio-demographic and contextual characteristics. Each characteristic is assigned a distinct effect on behavioral outcomes (e.g. the level of income determining implicit hurdle rates used for investments and no decision regarding insulation being made by tenants). A study by Sachs et al. [87] implements actor heterogeneity in MUSE, incorporating thirteen groups based on socio-demographic characteristics in the model's residential sector module. In ABMoS-DK, a desired number of agents can be generated

through a probabilistic approach using Monte Carlo Simulation. Generated agents are then matched with existing data regarding energy demand and demographic characteristics. The most detailed account of heterogeneity is provided by HESTIA, since a distinction can be made on the basis of contextual and socio-demographic characteristics of individual Dutch households.

5.2.3. Empirical and theoretical foundation

The extent to which models rely on behavioral data represents a continuum, ranging from models not relying on any empirical findings to models directly including behavioral data. Models which do not incorporate empirical data represent conceptual approaches which can show how behavior can possibly be included in ESMs (e.g. IESA-sim and ENSYSI). Without supporting assumptions by means of empirical findings, however, behavioral realism cannot be guaranteed.

In other ESMs, some empirical evidence is used either in support of behavioral assumptions or to establish actor heterogeneity (PRIMES, MARKAL-MACRO, TIMES Households model, MUSE, CIMS, ESME, CA-TIMES, TIMES-IR & CA, TIMES-DKEMS, MoCho TIMES). For instance, the TIMES Households model distinguishes actor categories based on the French national housing and transport survey. Discount rates implemented in models are often based on prior findings regarding consumers' purchasing behavior [80,83,99]. The studies relied on, however, might be conducted in a differing time and place compared to the modelling context, which may weaken the data's relevance.

Few ESMs directly incorporate empirical findings from existing studies, usually conducted in the (geographic) modelling context (BLUE, CIMS, ABMoS-DK, HESTIA, UK TIMES). Verrier et al. [45] rely on results of a qualitative survey regarding peoples' heating technology preferences (BLUE) and Mau et al. [90] implement data from discrete choice surveys regarding preferences for hybrid gas-electric vehicles or hydrogen fuel cell vehicles (CIMS). ABMoS-DK incorporates data in the form of existing travel behavior from the Danish National Travel Survey. Such approach ensures the modeled behavior to be closely aligned with the behavioral reality in the modelling context.

The modelling of behavior in most of the ESMs is not explicitly guided by theoretical insights. Implicitly, models that account for adoption decisions often rely on bounded rationality theory by assuming investments not to follow purely cost-optimizing pattern and agents to base their decisions on limited information [12]. Besides, some models rely on Rogers' theory of innovation adoption [37] (IESA-sim, BLUE, ENSYSI). In contrast to BLUE, IESA-sim and ENSYSI modify and only partly implement the original theory, which may alter the theory's fundamental meaning.

5.2.4. Modelling approach

The majority of ESMs selected for the review is optimization-based, which is in line with this approach being used most frequently in energy system modelling [71]. Considering only the models which include behavior in both sectors (i.e. without considering the case studies), as much as half of the models are simulation-based (mostly ABMs), indicating a strong reliance on this modelling approach for a holistic incorporation of behavior. Optimization ESMs were found to account for actors' behavioral preferences mostly in terms of financial aspects of adoption decisions (e.g. varying hurdle rates). More detail regarding drivers of behavior (e.g. attitudes and values) as well as social influences on behavior was included in simulation-based ESMs, especially ABMs. However, while some ABMs include agent interaction in an indirect manner (for instance through overall sector developments, see ABMoS-DK), no model accounted for direct interactions between actors.

Independent of their overall modelling approach, ESMs can show simulating or optimizing patterns in their demand-side modules. For instance, ABMs may include cost-optimizing rules for agent decisions and energy demand in optimization models may be simulated based on technology diffusion curves. To elucidate such level of detail for each of the included ESMs, Appendix D provides a description of how adoption

decisions and energy service use are determined per model.

5.3. Conclusion of review

The review showed that behavior in current ESMs is commonly included in terms of the appraisal of technologies and energy services, socio-demographic aspects, and contextual drivers. Energy service use was considered exclusively with regards to financial and contextual aspects. Some more variety in the drivers of behavior was observed for the modelling of adoption decisions. Overall, less attention is being devoted to the remaining drivers of behavior (pro-environmental, familiarity, social). For instance, social drivers are currently mostly represented indirectly and through external assumption. Thus, the analysis implies that there is much space for improvement regarding a holistic account of behavioral drivers in ESMs.

Methodologically, the review revealed a scarce reliance of models on relevant empirical findings regarding behavior. While most of the reviewed models mention some empirical findings guiding their incorporation of behavioral aspects, there are only a few examples of ESMs directly incorporating empirical data of studies conducted in the desired modelling context, thereby ensuring accuracy and realism of the included behavioral patterns. Most ESMs also acknowledge that behavior tends to differ between individuals and households and attempt to account for some of this variation by forming various actor groups with differing behavioral patterns. Some models address potential changes of behavior over time, albeit usually conceptual in nature rather than empirically founded.

Regarding modelling approaches, the high number of reviewed ESMs being simulation-based is notable, considering that the vast majority of models in the energy sector is optimization-based. This finding may confirm the relatively higher suitability of simulation models for including behavior due to their flexibility for exploring future states of the energy system, rather than focusing on the optimization of (usually) system costs. The insights from the review of ESMs are next synthesized with the existing social science literature described in section 2 to arrive at approaches for advancing the behavioral representation in ESMs.

6. Operationalizing behavioral drivers in ESMs

6.1. Prioritization of relevant and feasible drivers

This investigation identifies various possible approaches for the representation of households and individuals in ESMs, summarized in Table 5. The different strategies were assessed according to their relevance and feasibility. The rating of relevance was established with regards to the reviewed social science literature in section 2. The rating reflects the importance of a respective behavioral driver for explaining energy-related behavior. Feasibility was determined based on the extent to which a driver can be measured and quantified, which represents a pre-requisite for inclusion in a model. The higher the feasibility, the easier it is estimated that a driver can be quantified and incorporated in an ESM. It must be noted that judgements of relevance and feasibility were made by the authors based on the information compiled in this paper. As both of these dimensions represent continua, the ratings should not be regarded as definitive but rather as relative judgements of the approximate position of the drivers on the continua.

Fig. 3 presents the drivers that were derived from both the social science literature as well as the model review according to their estimated relevance and feasibility. Rather than displaying drivers' absolute positions, the Figure is presented to provide guidance regarding which drivers to prioritize, as drivers that combine a high feasibility and relevance (upper right quadrant) can be considered a starting point for implementation in ESMs (see Table 5 for more detail on those dimensions per driver category). If a driver is placed towards the right side, it is estimated that the driver can be measured with pre-defined questionnaires (e.g. values) or it is commonly measured in surveys

Table 5
Possible approaches to incorporate behavioral drivers in ESMs.

Driver category	Behavioral outcome	Modelling options	Data needs	Feasibility	Relevance
Pro-environmental drivers	Adoption of technologies influenced by pro-environmental values, attitudes/beliefs, or behavioral intentions	- Discount rates/intangible costs/ratings based on technologies' actual or perceived environmental performance (e.g. perceived sustainability, CO₂ emissions) and actors' pro-environmental values, attitudes/beliefs, or behavioral intentions (e.g. BLUE [88], IESA-sim, [84]) - Probability to invest in technologies depending on the technologies' actual or perceived environmental performance (e.g. perceived sustainability, CO₂ emissions) and actors' pro-environmental values, attitudes/beliefs, or behavioral intentions (e.g. PRIMES [80])	- Self-reported pro-environmental values/attitudes/beliefs/behavioral intentions linked with data on technology adoption - Environmental performance of technologies/self-reported perception of environmental performance of technologies	Medium (Self-report) measures of values, attitudes, beliefs, and behavioral intentions exist (regarding values, see e.g. Refs. [100,101]). Longitudinal studies indicate values be relatively stable over time [102]. This relative stability makes values specifically feasible to be included in ESMs, since no potential changes must be considered.	Medium – High Studies confirm the predictive qualities of pro-environmental drivers. Attitudes, beliefs, (personal) norms and behavioral control may exert their impact on energy-related behavior through behavioral intentions (see TPB). To investigate a potential intention-behavior gap [18], the drivers should directly be related to behavioral outcomes (i.e. energy service use and technology adoption). Contextual aspects should be taken into account when investigating values due to potential confounding effects [20].
	Energy service use influenced by pro-environmental values, attitudes/beliefs, or behavioral intentions	Function of change in energy service use as a result of actors' pro-environmental values, attitudes/beliefs, or behavioral intentions (authors' suggestion)	Self-reported pro-environmental values, attitudes/beliefs, or behavioral intentions linked with actors' energy consumption		
Appraisal of technologies and energy services	Adoption of technologies influenced by their (perceived) characteristics	Discount rates/intangible costs/ratings based on selected characteristics of technologies (e.g. speed, complexity) (e.g. MARKAL-MACRO [83], IESA-sim [84], PRIMES [80])	- Assessment of characteristics being considered important for adoption decisions - Self-reported rating of selected characteristics per technology linked with data on technology adoption	Medium – High Ideally, respondents should be asked about the technology characteristics that they consider important for their adoption decisions. Determining price elasticities is usually feasible and requires an analysis of changes in demand in relation to changes in energy prices. If data is unavailable, previous research can be considered (see e.g. Ref. [42]).	Medium – High The perception of technologies and energy service use has been shown to be a relevant factor for energy-related behavior. As actors' perceptions of costs and other characteristics of technologies and energy services may differ between technologies and energy services [42], one should distinguish different technologies and energy services during data collection and analysis.
	Actors' cost perceptions (i.e. sensitivity to changes in energy prices)	Price elasticity of demand (e.g. PRIMES [80])	Actors' energy consumption over time linked with energy prices over time		
Familiarity	Past/present experiences impacting (future) technology adoption	- Agent decision rules: In case of equal cost/utility, choose technology which you currently own or have previously owned (e.g. ABMoS-DK [97]) - Using existing market share of technologies to predict future market share while limiting the replacement of existing technologies according to individuals' stated preferences (e.g. BLUE [45])	Self-reported/actual past technology ownership or self-reported/actual present technology ownership linked with self-reported future technology choices/preferences	Medium – High Data regarding existing and past technology ownership and energy service use may be available in public databases	Medium – High Familiarity has been shown to influence energy-related behavior. Specific attention should be paid to utilizing data collected in the specific modelling context, as these aspects tend to be strongly related to cultural influences [103].
	Habits impacting energy service use	Keeping energy service use constant over time (authors' suggestion)	Actors' energy service use over time		
Socio-demographic drivers	Adoption decisions or energy service use driven by socio-demographic aspects	Determining patterns of adoption decisions/energy service use based on: - Income - Gender - Age - Education level - Dwelling ownership status - Marital status - Household size - Employment - Car availability	Socio-demographic data linked with actors' data on technology adoption and/or energy consumption	High Socio-demographic data is often available in public databases. Depending on the context, there may also be previous research findings linking socio-demographic aspects with energy-related behavior (e.g. Refs. [22,50]).	Medium While socio-demographic aspects have been shown to exert influence on energy-related behavior, mixed findings have been reported regarding their relative importance.

(continued on next page)

Table 5 (continued)

Driver category	Behavioral outcome	Modelling options	Data needs	Feasibility	Relevance
Social drivers	Social norms impacting technology adoption	These aspects can be included in ESMs following a variety of approaches (e.g. defining age groups, household sizes, etc.) (e.g. TIMES Households Model [82]). - Injunctive social norms: Discount rates/intangible costs/ratings based on technologies' perceived social desirability (e.g. ENSYSI [85]) - Descriptive social norms: Determining a function of change in adoption of technologies on top of expected changes due to changes in technologies' costs (e.g. CIMS [90])	- Self-reported social perceptions of technologies (injunctive norms) linked with data on technology adoption - Existing technology choices of individuals and households in a neighborhood (descriptive norms) linked with data on technology adoption - Rating of visibility of others' technology adoption	Medium Measurements of social norms exists (e.g. Ref. [104]). Data of descriptive norms may often be available in public databases (e.g. number of purchased technologies, choice of transport mode, level of energy consumption). Data collection regarding injunctive norms can be more labor intensive, as self-reports must be collected regarding peoples' perceived social desirability of certain technology choices or patterns of energy service use.	Medium – High Social influences have been shown to be predictive of energy-related behavior. Since individuals and households perceive social norms within their immediate surroundings, data should ideally be considered per area or neighborhood. The impact of social norms may also differ between different technologies and energy services, as the perception of descriptive and injunctive norms partially depends on the visibility of technologies and energy service use of others.
	Social norms impacting energy service use	Function of change in energy consumption as result of (diffusion/change of) social norms (authors' suggestion)	- Self-reported perceptions of social norms regarding energy consumption (injunctive norms) linked with actors' energy consumption - Existing energy consumption data of individuals and households in a neighborhood (descriptive norms) - Data regarding visibility of others' energy consumption.		
Contextual drivers	Adoption decisions or energy service use influenced by contextual aspects (e.g. infrastructure)	Determining patterns of adoption decisions/energy service use based on: - Infrastructure (e.g. place of residence, coverage of transport system) - Environmental conditions - Building characteristics - Policy-related incentives These aspects can be included in ESMs following a variety of approaches (e.g. adjusting technology preferences based on location of residence (ABMoS-DK [97])).	Contextual data linked with actors' technology adoption and/or energy service use	High Aggregated contextual data is often available in public databases.	Medium – High Contextual drivers have frequently been related to energy-related behavior

Note. This table does not offer an exhaustive list of all possible drivers and approaches. The final choice of the most suitable behavioral drivers as well as modelling approaches will vary depending on the specific model structure, the modelling purpose, the behavior(s) of interest, and the modelling context. Some work has been done in mapping more detailed strategies for either the residential or transport sector (e.g. Ref. [105]), which may serve as further inspiration.

already (e.g. socio-demographic aspects).

When implementing a set of behavioral drivers in an ESM, it is important to consider if and how these drivers might relate to each other and which potential confounding variables may play a role [20]. For instance, studies have shown that behavioral intentions can act as mediators between other drivers and behavioral outcomes and that modifications of social norms can exert an impact on personal norms, attitudes, and beliefs [26]. Such relationships should be tested and incorporated to safeguard the accuracy of the modeled behavior. Apart from the aspects described in section 2, further socio-demographic and contextual variables may be relevant to consider depending on the sector, the respective modelling context, and the modelling aim. Socio-demographic drivers may also represent proxies for other underlying drivers of behavior. If data is available, mediation analyses can provide insights into the mechanisms through which socio-demographic aspects may impact energy-related behavior.

6.2. Methodological aspects

When including behavior in an ESM, modelers must find an appropriate balance between behavioral and technological detail. Some ESMs were found to incorporate rich technological information, albeit considering behavior in a simplified manner. Other models included more behavioral detail, but less technological information. In both cases, relevance of the modelling outcomes for policy making should be considered, as detailed insights about potential technological developments as well as the effect of energy-related behavior may be required. This aspect was also highlighted in the interviews. Based on this analysis, MUSE, IESA-sim, ENSYSI, and the TIMES Households model present examples of models that simultaneously account for rich technological and behavioral detail.

It must be noted that a tradeoff exists between increased behavioral detail and augmented modelling complexity. Increasing behavioral detail in one sector can also lead to imbalances between other sectors which may be modeled in a more aggregated fashion. Therefore, it is

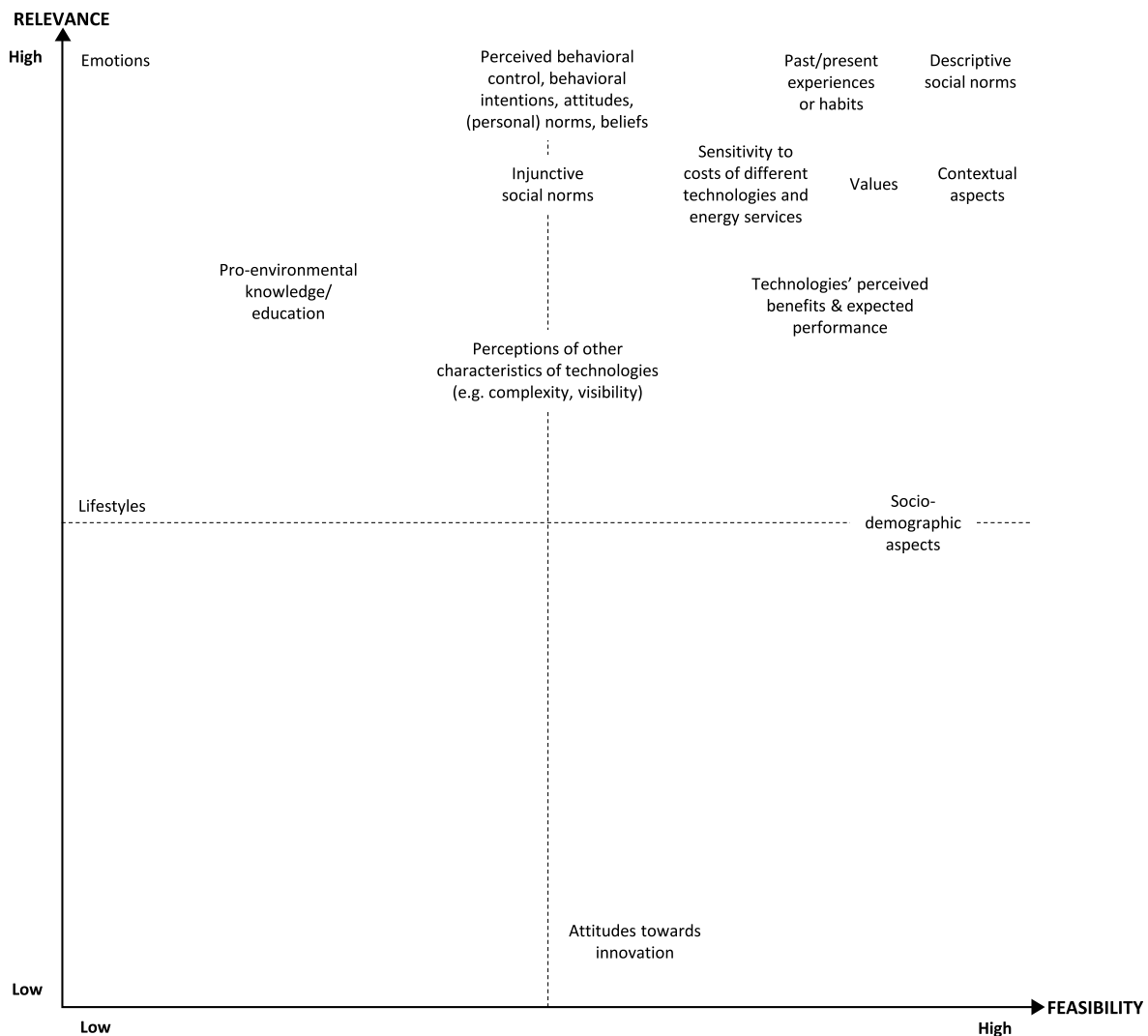


Fig. 3. Relevance and feasibility of including drivers of energy-related behavior in ESMs.

suggested to carefully consider the detail of technological and behavioral representations of all included sectors and computational limitations to ensure a balanced inclusion of behavioral aspects. Other methodological considerations emerged from the review, which are described in the following sections.

6.2.1. Longitudinal approach

Some behavioral tendencies are relatively stable, others can undergo modifications over time. For instance, while values tend to be relatively consistent, attitudes, beliefs, and intentions have been shown to be more variable [106]. If previous research indicates drivers to change over time, longitudinal data can be helpful to assess the rate and extent of such proposed changes. This type of data does imply increased time and effort requirements, which need to be weighed against the relative ease of cross-sectional data collection.

Regarding specific behavioral change phenomena, previous research has proposed rebound effects to be incorporated in models [43,44]. Social tipping points have also been suggested to be included in modelling efforts due to the notions' potential for capturing social transformation dynamics [107]. However, the fact that social tipping points have not yet been extensively researched and consistently conceptualized compromises their feasibility of measurement [108]. If desired, social tipping points could be explored in models by means of various scenarios in which different behavioral change patterns or tipping point thresholds can be defined (see e.g. BLUE [88], where such

approach is shown with pro-environmental values).

Any implementation of behavior changes in models, even if based on prior longitudinal findings, requires assumptions about the future to be made, which inherently yields uncertainties. Thus, in line with approaches observed in current models, it may be useful to consider the modelling of behavior changes as explorative attempts, which can be investigated through different behavioral modification scenarios. Based on the present review, there are various approaches to be considered for such exploration (see Table 6). Specifically ABMs may lend themselves for a dynamic accounting of behavioral changes over time due to their flexible structure. For instance, learning can be incorporated in ABMs relatively easily through defining agent rules and characteristics (e.g. ABMoS-DK [97]). Incorporating behavioral change phenomena, however, increases the complexity of model results and should carefully be considered in light of model usability, interpretability and communicability.

6.2.2. Actor heterogeneity

In line with prior literature, including various actor groups in ESMs is important to account for differences in actors' behaviors [2,10, 109–111]. In principle, if sufficient data is available, any (set of) behavioral driver(s) can be used to distinguish actor groups (e.g. income, strength of pro-environmental value orientation). Alternatively, one can generate a desired set of random agents through a probabilistic approach and calibrate these agents with existing empirical data (e.g.

Table 6

Possible approaches to incorporate changes in behavior over time in ESMs.

Behavior to be represented	Modelling options	Supporting data sources
Changes of adoption decision patterns	• Modification of existing distribution of attitudes/beliefs/behavioral intentions among actors (e.g. BLUE [88]) • Rate of diffusion of certain decision objectives (e.g. diffusion of pro-environmental values; e.g. BLUE [45]) • Determining a change in perceived characteristics of technologies over time (e.g. increasing social acceptance of technologies with increasing market share; authors' suggestion)	• Self-reported (changes in) attitudes/beliefs/intentions (longitudinal data) linked with actors' technology adoption and/or energy consumption • Assessment of diffusion of (self-reported) decision objectives among actor groups (longitudinal data) linked with actors' technology adoption and/or energy consumption • Self-reported (rating of) characteristics of technologies being considered important for adoption decisions (longitudinal data) linked with actors' technology adoption and/or energy consumption
Changes of patterns of energy service use	• Diffusion of certain consumption patterns over time (e.g. decreasing energy consumption for heating over time due to increasing awareness of energy savings measures; authors' suggestion)	• Self-reported or actual energy consumption patterns over time
Structural overall changes of behavioral patterns after a certain threshold due to (changing) social norms (i.e. social tipping points)	• Determining a threshold after which behavior structurally changes (i. e., social tipping point) and determining how behavior changes (i.e. which driver(s) become more prominent; e.g. BLUE [45])	• Assessment of trigger points/thresholds for social tipping points regarding energy-related behavior linked with actors' technology adoption and/or energy consumption • Qualitative or quantitative assessment of underlying dynamics of structural changes in energy-related behavior (e.g. surveys, interviews, observations)
Rebound effects (i.e. increase in service use after a new technology/an energy saving measure has been implemented)	• Rate of decrease of expected energy savings after implementation of a measure which saves energy or uses renewable energy (authors' suggestion)	• Data on energy consumption over time linked with actors' technology adoption

ABMoS-DK [97]). A main challenge then lies in establishing useful actor categories which can account for meaningful behavioral differences. Thus, it is important to assess which drivers are most relevant for explaining behavior in the respective modelling context. Accounting for heterogeneity also requires behavioral patterns to be defined per agent group, which necessitates sufficient empirical findings that can be used as a basis for such definition.

A decision regarding the number of actor groups depends on the desired behavioral granularity as well as available computational capacity. Thereby, one can start with the implementation of a limited

number of agents and add more heterogeneity incrementally. This process ensures a careful consideration of the tradeoff between augmented behavioral detail and the increased complexity of an ESM [112,113]. As a high level of complexity can compromise model usability, the effect of behavior on the model output should first be understood before incrementally adding actor groups.

6.2.3. Empirical and theoretical foundation

From this review, it emerges that the empirical foundation of the behavior of households and individuals in current ESMs is relatively weak. This finding may partially be explained by a scarcity of available data, as also indicated by the interviewees. While conceptual ESMs still allow for exploring the effects of behavior on the energy system, empirical findings are essential to ensure behavioral realism [2]. Therefore, improving the strength of empirical foundation is of major importance for advancing the inclusion of realistic behavior in ESMs.

ESMs included in the review that directly incorporate empirical findings rely on cross-sectional data measuring choices, preferences, or travel patterns (see section 5.2.3). This data is utilized to derive underlying drivers of behavior and establish heterogeneity. Longitudinal data is not mentioned, which is likely due to lack of availability and increased collection efforts. The collection of behavioral data should be matched with the geographic scale of the remaining (technological, economical, etc.) data included in an ESM, since behavioral patterns might differ between settings, contexts, and cultures [92,103]. Such approach implies that ESM results apply to a specific modelling context and cannot readily be generalized to other geographic locations.

Any incorporation of behavior in an ESM necessitates a clear conceptualization of energy-related behavior and its different predictors. Such conceptualization can be supported by available social science theories (for a sub-set of available theories see Table 1 and Appendix C). The TPB has frequently been implemented in models due to its simplicity and the relative ease with which it can be translated into code [114–116]. Regardless of the selected theory or set of theories, a central task revolves around the empirical validation of proposed relationships between behavioral drivers and outcomes. Empirically validated drivers can subsequently be incorporated in ESMs through appropriate formalization, operationalization, and quantification of a theory's concepts [116]. Thereby, Muelder and Filatova [116] emphasize the need for informed decision making as well as transparency, since differences in the implementation of a theory can result in diverging model outcomes.

6.2.4. Modelling approach

According to some of the interviewees, implementing behavior in ESMs can be challenging as modelers often have to modify the structure of an existing ESM and translate descriptions of behavior, which are often qualitative, into mathematical formulations. This finding is in line with Trutnevyte et al. [13], stating that merging social science findings with existing ESMs tends to be a demanding endeavor. Despite potential obstacles, the authors still emphasize that a merging approach has the highest potential for improving models' behavioral realism.

This review has highlighted the value of simulation modelling due to providing more diverse options for accounting for behavioral drivers. Thereby, ABM might be particularly suitable, as behavioral drivers can be included through defining flexible agent rules. For instance, to incorporate habits, agents can be set to re-select their current technology if a certain (pre-defined) threshold of difference regarding costs or utility has not been transgressed (e.g. ABMoS-DK [97]). ABMs can also account for interaction dynamics, which makes the approach a particularly suitable technique for endogenously modelling social dynamics [2,73,117]. For instance, social norms can be translated into defining specific agent network characteristics and the strength of social influences [115].

In addition to focusing on standalone ESMs, the results of different models can be compared. Fattahi et al. [4] note that contrasting the

results of (comparable) simulation and optimization ESMs can provide insights into differences between an optimal solution and a simulated feasible solution. ESMs can also be linked with other models [2,9,118]. For instance, behavior-related parameters of optimization models can be informed with findings derived from simulation models [105]. Such linking processes can be used as long as the models share some key characteristics, and may save time and avoid potential complications arising from the full integration of behavioral findings into existing ESMs [2]. Such soft-linking approach is exemplified by Ramea et al. [119], integrating insights derived from a model simulating consumers' vehicle choices into the optimization-based ESM TIMES.

7. Discussion

ESMs differ in their fundamental modelling purpose [4,5]. The insights of this work are aimed at improving the behavioral realism of models with exploratory and/or descriptive purpose that aim at generating insights into possible transition pathways. ESMs following a normative or prescriptive purpose, in contrast, place higher importance on outlining a future state of the energy system and it may therefore be less relevant to incorporate increased behavioral detail into such ESMs.

The review shows that various drivers impact energy-related behavior and that different approaches can be taken to incorporate behavioral drivers in ESMs to enable an improved and more realistic description and exploration of pathways towards a decarbonized energy system. Currently, the most common way to include adoption decisions in ESMs is through the present or future costs of technologies, and the most frequent manner to account for energy service use is through price elasticities of demand [3,42]. Several models further consider socio-demographic aspects and contextual drivers of behavior. While such ESMs can serve as a starting point, a comprehensive consideration of the six categories of empirically-based drivers impacting energy-related behavior (i.e. pro-environmental drivers, appraisal of technology and energy services, familiarity, socio-demographic drivers,

social drivers, contextual drivers, see section 2) is lacking. This underrepresentation confirms the need for advancement and potential for expanding the behavioral modelling of households and individuals [2, 3].

For behavior to be incorporated, human cognitions and actions must be translated into mathematical formulations that can be implemented in models. Despite the overall underrepresentation of many drivers of behavior, several ESMs have done innovative work, for instance by accounting for pro-environmental values, habits, and social influences [85, 88,97]. These approaches are valuable in providing a starting point to further develop the modelling of behavior in ESMs. This work identifies a series of steps to be taken when implementing behavior in an ESM (as displayed in Fig. 4), building on the merging strategy proposed by Trutnevyte et al. [13] (i.e. the structural adaptation of ESMs according to social science findings). Based on these steps, Fig. 5 gives an overview of state-of-the-art practices and feasible advancements.

The first step for implementing behavior in an ESM consists of data collection. Most ESMs represent a reasonable level of detail regarding behavioral outcomes (i.e. technologies and energy service uses in residential and transport sector), but do not explicitly incorporate data regarding behavioral drivers impacting these outcomes. Partly, this observation can be explained by the scarce availability of behavioral data, which currently entails a major limitation. Increasing data collection efforts can ensure a thorough empirical basis regarding both behavioral drivers and outcomes, which is imperative for advancing the modelling of behavior in ESMs [2]. This analysis provides guidance regarding the relevance and feasibility of including different drivers (see Table 5 and Fig. 3), which can be used as a tool to determine prioritization. Ultimately, the choice of behavioral drivers should depend on the modelling aim, the modelling context, and data availability. Thereby, augmented behavioral detail should carefully be weighed against increased model complexity.

The second step, the preparation of the model, requires an analysis of empirical data regarding behavioral drivers and behavioral outcomes to

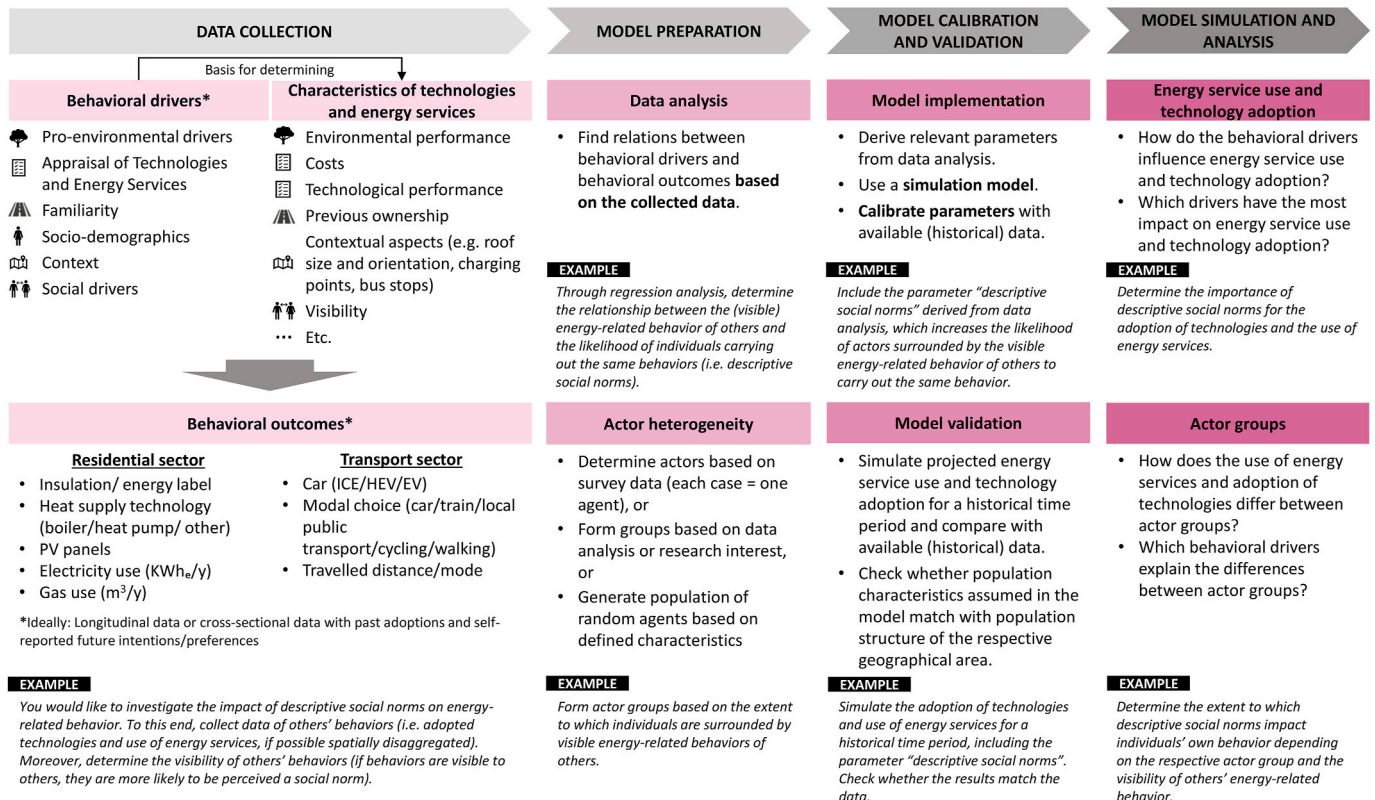


Fig. 4. Steps for incorporating behavioral aspects in an ESM.

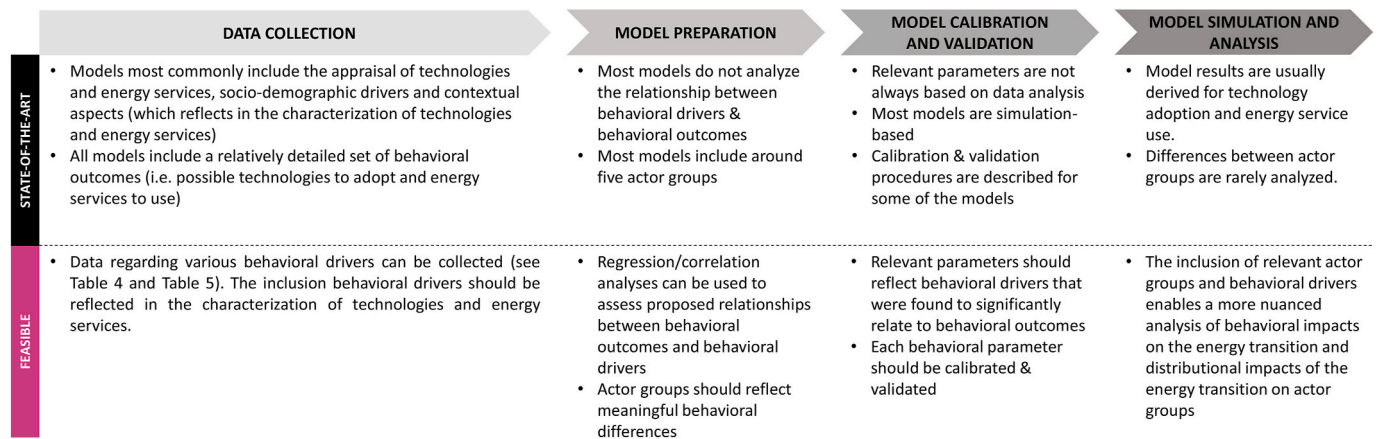


Fig. 5. State-of-the-art and feasible extensions of the steps for incorporating behavioral aspects in an ESM.

determine the relationship and the relative impact of the drivers on the outcomes. For instance, correlation and regression analyses can be used to determine the direction and strength of the relationship between drivers and outcomes as well as the relative predictive power of individual drivers in relation to others. The drivers chosen based on this analysis should then guide the characterization of technologies and energy services. For instance, if pro-environmental values are incorporated, the (perceived) environmental performance of technologies and energy services must be determined. To arrive at one behavioral outcome (i.e. an adoption decision or the level energy consumption), drivers must be combined. Different methods are available to accomplish such combination, for instance the formation of a weighed sum or ordering drivers by priority (see Table 5).

To account for behavioral heterogeneity, actor groups must be defined [2,109,110]. The review shows that it is common practice to rely on four to five groups, such as actors with differing incomes or pro-environmental values. Particularly distinguishing groups by socio-demographic and contextual aspects can provide important information regarding the characteristics and surroundings of households and individuals. A greater number of actor groups enables more detailed behavioral analyses, but must be weighed against model complexity to ensure that the model remains sufficiently simple and understandable. More detailed approaches also require sufficient empirical data, allowing for a distinction of behavioral patterns and a weighing of different drivers between actor groups.

The third step involves the implementation of behavioral data into an ESM, for which the use of simulation modelling (e.g. ABM) is suggested. Reviewed models that incorporated behavior in the most advanced way were simulation-based, confirming this approach to be comparably more flexible and suitable for exploring possible future states of the energy system [9,74,75]. Several tools are available to summarize the information derived from different behavioral drivers into modelling the behavioral outcomes, such as rating technology options, determining intangible costs or including price elasticities (see Table 5). Model parameters should be calibrated and the model should be validated by using historical data regarding behavioral outcomes, as exemplified by Ref. [120]. In the last step, model results can be analyzed per technology and per actor group and the changing of individual model parameters allows for exploring the relative impact of specific behavioral drivers on model outcomes.

Such analyses are urgently needed to gain further insights into the drivers and pathways to accelerate the energy transition. Behavior has been highlighted to be an important enabler of the transition [6,7], and an explicit investigation of realistic behavior in ESMs will shed light on the relative impact of behavioral drivers on desired behavioral outcomes (i.e. the adoption of renewable technologies and changing patterns of energy consumption). At the same time, the energy transition exerts

major impacts on individuals' livelihoods [121]. A more targeted definition of actor heterogeneity allows for distributional effects to be taken into account; for instance, one can analyze potential differences in technology adoption rates and energy service use between societal groups. In line with energy justice [122], such insights can guide informed decisions of policy makers to ensure that no societal group is left behind in the energy transition [1,6].

It must be noted that in the process of including behavioral drivers into ESMs, more detail is not always better: Augmented behavioral detail in ESMs enables a deeper and more realistic analysis of transition pathways, but must carefully be weighed against increased requirements for model inputs and enlarged complexity of model outputs. By nature, ESMs are intended to show a simplified version of the reality of the energy system. It is therefore recommend to add behavioral detail to an ESM incrementally, ensuring inputs to remain manageable and results to be understandable, insightful and communicable.

There are three methodological considerations of the present work, arising from the scope of the review requiring choices to be made regarding the level of detail of the analysis. Relevant social science knowledge served as background of the work and was summarized from existing reviews and meta-analyses, rather than carrying out an own review effort targeted to the specific analysis. Despite the search process combining a systematic approach with interviews, some relevant ESMs might have been missed. Regarding the selected ESMs, there were large differences in terms of clarity and length of documentation, which might have led to some information being omitted from the analysis. While this review provides a comprehensive overview, future work could tackle these methodological aspects to assess the behavioral modelling of ESMs in even more detail.

The review findings show that more work is needed to further lower the barriers for explicitly addressing drivers of human behavior in ESMs for the purpose of describing and exploring transition pathways [9,10]. The suggested approaches (see Table 5) are intended to serve as inspiration and guidance for modelers to increase ESMs' behavioral realism. Future work should employ an interdisciplinary approach, which can be achieved through increased collaboration and dialogue between social scientists and energy modelers. Research should also rely on data-driven strategies and a thorough analysis of behavioral drivers and their relationships with behavioral outcomes (e.g. through correlation/regression analysis). Behavioral data should be collected in the respective modelling context to ensure applicability. Actor heterogeneity, which tends to exert large impacts on modelling results [120], should carefully be determined based on meaningful differences between actors in the drivers of energy-related behavior. The analysis has shown that it is currently common practice to include at least five actor groups, often based on socio-demographic and contextual characteristics. A major limitation regards the availability of empirical data, which is needed to

derive such relevant behavioral patterns and distinguish meaningful actor groups. This shortcoming should be tackled by future work through targeted data collection efforts that allow for connecting behavioral drivers and outcomes on the level of households or individuals.

8. Conclusion

To enable a successful energy transition, a holistic assessment of drivers and barriers is needed. Energy System Models (ESMs) present indispensable tools for investigating transition pathways. Current models insufficiently account for realistic human behavior, despite the fact that human behavior has been shown to exert a major impact on the energy transition [6]. This research presents a multitude of approaches to foster the inclusion of human behavior for informing current ESMs with insights from social science research. Suggested approaches revolve around data-driven strategies, highlighting the importance of empirical data collection regarding all behavioral drivers and behavioral outcomes included in a model. The consistent use of data also enables an analysis of proposed relations between behavioral drivers and outcomes, which is necessary to safeguard models' behavioral realism. This study has further highlighted the value of simulation modelling for representing behavior as well as the importance of accounting for meaningful behavioral differences through defining actor heterogeneity.

Based on the analysis, it is recommended to improve the integration of realistic behavioral aspects through a strong reliance on empirical data regarding both behavioral drivers (i.e. pro-environmental drivers, appraisal of technology and energy services, familiarity, socio-demographic drivers, social drivers, and contextual drivers) and outcomes (i.e. adoption of technologies and energy service use). Besides the appraisal of technologies and energy services, which is commonly included in ESMs, next targets may for instance entail descriptive social norms as well as socio-demographic and contextual aspects due to frequent data availability and relative ease of inclusion. In general, to confirm the relevance of any (set of) behavioral drivers, one should start with an explicit investigation of the relationships between behavioral drivers and outcomes in the respective modelling context (e.g. correlation/regression analysis).

When representing individuals' and households' behavior in an ESM, it is essential to define actor heterogeneity to capture behavioral differences and analyze distributional impacts of the energy transition. Meaningful actor groups can be delimited based on findings from data analyses or research interest. Alternatively, representative respondents from surveys can form a set of agents which can be incorporated in an ESM directly. The availability of empirical data regarding behavior presents a major limitation to date, which should be tackled in the future

through extended (cross-sectional or longitudinal) data collection efforts. Future studies should aim to collect data of both behavioral drivers and outcomes on the level of households or individuals to be able to assess the direct relationships between behavioral drivers and actual behavior.

The recommendations of this study are fundamentally intertwined with the respective modelling purpose. While ESMs can offer accurate or normative forecast of a future energy system without accounting for human behavior, an advanced integration of behavior is urgently needed to enhance the accuracy of those models that aim to shed light on possible transition pathways [10]. An increased focus on behavior in energy system modelling also directs attention towards social impacts and energy justice issues of the energy transition, which are currently often overlooked due to a predominant focus on technological advances [11]. Future interdisciplinary work building on the insights of this analysis is indispensable to further foster the consideration of behavioral aspects in the planning of the energy transition. It is recommended for such work to use the outlined series of steps to model relevant and feasible drivers of energy-related behavior as a starting point.

CRedit authorship contribution statement

H.S. Galster: Conceptualization, Methodology, Investigation, Writing – original draft, Writing – review & editing, Visualization, Project administration. **A.J. Van der Wal:** Conceptualization, Methodology, Writing – review & editing, Supervision. **A.E. Batenburg:** Conceptualization, Methodology, Writing – review & editing, Supervision. **V. Koning:** Conceptualization, Methodology, Investigation, Writing – review & editing, Visualization, Supervision, Project administration. **A.P.C. Faaij:** Conceptualization, Methodology, Supervision, Funding acquisition, Project administration.

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.

Acknowledgements

This work was financially supported by the Dutch Organization of Applied Scientific Research (TNO). This research has benefitted from conversation with Prof. dr. Neil Strachan, Dr. Brunilde Verrier, Prof. dr. Evelina Trutnevyte, Dr. Sabine Pelka, Prof. dr. Laurens de Vries, and Dr. Sara Giarola, and the authors thank them for their contribution to the present work.

Appendix A

Semi-structured interview questions

Questions about own model

- How did you decide for the main behavioral parameters ?
- To what extent did you rely on empirical data? What were potential challenges you faced when including data into the model?
- In general, what were the main challenges you faced when incorporating behavior into the model?
- Are there any other behavioral aspects you would still like to include into the model?

Questions about behavior in ESMs in general

- Do you know of any other (national) ESMs including behavior of individuals and/or households?
- In your view, what is needed to advance the modelling of behavior in ESMs?
- What would you recommend to focus on when including behavior into ESMs?

Appendix B

Main interview findings

Main challenges regarding the modelling of behavior

- Availability of behavioral data
- Empirical validation of behavior in ESMs
- Uncertainty of human behavior
- Behavior tends to create inertia in the energy system
- Translation of verbal agent descriptions into mathematical formulations
- Thorough understanding of (potentially) complex model results

Aspects to consider when integrating behavior in ESMs

- Important to maintain a balance between behavioral and engineering aspects in the model
- Heterogeneity tends to exert large impact on model results
- Best practices and desirable approaches may depend on modelling context/country

What should be done to improve the integration of behavior in ESMs?

- Improved data availability regarding intangible aspects of behavior
- Inclusion of behavior despite potential uncertainties
- Inclusion of multiple aspects of behavior linked with empirical data
- Empirical validation of model results (e.g. use of historical data)
- Summary of best practices regarding the inclusion of behavior in ESMs
- More realistic accounting of social influence/social interaction in models
- Accounting for changes in behavior over time (requires collection of longitudinal data)

Appendix C

Social science theories

Table C.1

Frequently mentioned social science theories in research regarding energy-related behavior.

Theory	Discipline	Description
Theory of Planned Behavior (TPB)	Psychology	The TPB by Ajzen [29] relates attitudes, norms, and perceived behavioral control to behavioral intentions, which in turn lead to behavior. While intentions are correlated with behavior, they only culminate in actual behavior if a person believes they can execute the behavior (i.e. possesses perceived behavioral control).
Reasoned Action Approach (RAA)	Psychology	The RAA by Fishbein and Ajzen [30] represents an extended version of the TPB. Concretely, the RAA specifies a set of beliefs (behavioral beliefs, normative beliefs, control beliefs) which influence attitudes towards a behavior, norms, and perceived behavioral control, respectively (as specified in the TPB).
Norm Activation Model	Psychology	The Norm Activation Model by Schwartz [32] poses that norms create moral obligations and are therefore necessary in causing behavior. The author further states that norms are determined by awareness, which leads to feelings of responsibility.
Value Belief Norm (VBN) Theory	Psychology	Stern's [33] VBN Theory presents an evolution of the Norm Activation Model. It revolves around three types of values (egoistic, biospheric, altruistic) impacting individuals' beliefs. These, in turn, are considered to influence personal norms that then determine behavior.
Self-Regulated Behavioral Change (SRBC) Model	Psychology	The SRBC by Bamberg [48] states that peoples' motivation to change enables behavioral change processes. Successful modifications of behavior are assumed to occur in a four-step process. First, people enter a predecisional stage which determines their goal intention. Second, a preactional stage establishes a behavioral intention. Third, during the actional stage, people put their behavioral intention to action. Last, a postactional stage establishes the new behavior.
Habit Discontinuity Hypothesis	Psychology	The habit discontinuity hypothesis describes that habitual behavior is most likely to be modified in conjunction with contextual changes [47]. Thus, once contextual conditions are disrupted, new choices and decisions are more likely to occur, making habit changes more probable.
Social Network Theories	Psychology/ Sociology	The family of social network theories (see e.g. Borgatti and Ofem [68]) investigates the impact of social relations on behavior. Thus, the focus lies on social network structures, group formations, etc.

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Table C.1 (continued)

Theory	Discipline	Description
Rogers' Theory of Innovation Adoption	Sociology	The Theory of Innovation Adoption [37] lists various attributes of technologies which are presumed to influence their adoption speed (i.e. relative advantage, compatibility, complexity, trialability, observability). The Theory also conceptualizes five adopter attitudes which are assumed to follow a normal distribution (i.e. innovators, early adopters, early majority, late majority, laggards).
Social Practice Theory	Sociology	The Social Practice Theory by Shove et al. [123,124] describes energy demand and supply as being ingrained with the reproduction of social practices. Thus, behavior is considered in relation to the social context (including societal practices, material arrangements, etc.) in which it is embedded.
Technology Acceptance Model	Information systems	In line with the TPB, Davis [36] regards behavior to follow from behavioral intentions. According to the author, intentions are determined by the acceptance of a certain technology as well as its perceived usefulness and perceived ease of use.
Bounded Rationality Theory/ Prospect Theory	Behavioral Economics	An integral aspect of economic theory centers around the rationality of individuals [125]. Thereby, neoclassical economics assumes people to make purely rational choices to "maximize utility subject to given market prices and income" ([38] p. 98). The Bounded Rationality Theory originated from the field of behavioral economics as a response to the neoclassical perspective, in an attempt to account for human limitations in decision making which result in non-optimal outcomes from a financial perspective [125]. Thus, instead of performing a complete cost-benefit analysis, the theory poses that people decide based on a subset of criteria, impacted by information available to them and subject to various cognitive biases.

Note. This table provides a brief summary of social science theories which are frequently mentioned in the literature regarding energy-related behavior. Thus, it does not give an exhaustive list of all theories that can be used to conceptualize energy-related behavior. Studies also often combine and/or modify various theories depending on the specific behavior and the specific context at hand.

Appendix D

Behavioral outcomes in models

Table D.1

Modelling of adoption decisions and energy consumption in ESMs

Model name	Adoption decisions	Energy consumption
TIMES Actor Model (TAM)	- Investment decisions in energy supply sector 3 actor types: citizens, institutional investors, utilities, with different hurdle rates to represent different time valuations of money and cost of capital - Actors have different choices of technologies (e.g. utilities cannot invest in citizens' rooftop PV) and budget restrictions - Actor-specific hurdle rate is included in the objective function of the model, which is used to calculate the total system costs and influences the model's technology choices - Citizens invest in energy supply technologies in the residential sector (e.g. rooftop PV)	Exogenous
PRIMES	Residential sector 5 income groups apply different discount rates for their investment decisions - Using these discount rates, actors strive for cost-optimization - Within each group of agents, a probability density function is used to assign probabilities to the most cost-efficient technologies. Agents can then, amongst others, make decisions among those technologies based on maximization of payback period or maximization of LCOE. Transport sector - Agent types can be distinguished through discount rates (not further described) - Intangible costs of technologies can be included, e.g. lack of availability of charging infrastructure for EVs - The model optimizes for a market equilibrium between demand and supply of transport services - Individual transport users maximize utility (derived from transport activity and through consuming goods and services unrelated to transportation) under income constraints	Residential sector - Demand elasticities: Energy demand can change in response to policies or energy price changes Transport sector - Overall transport activity (which determines demand) is projected based on macroeconomic drivers - Modal shift is possible to some degree, explicit options can be included in scenarios
CA-TIMES	- One central decision maker, cost-optimization - Higher discount rates for newer (less mature, more uncertain) technologies to account for consumers' hesitance to invest in such technologies - No distinction is made between behavior in the residential and transport sector	Exogenous
TIMES Households model	- Minimization of overall system costs Residential sector 180 household segments distinguished - Some technology constraints (e.g. only homeowners can invest in insulation) - Households use different hurdle rates in their investment decisions and face different capital constraints	Residential sector Determined per household segment based on: space-living area, insulation, income (determining a "service factor" used to calculated final demand), household size

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Table D.1 (continued)

Model name	Adoption decisions	Energy consumption
	Transport sector	Transport sector
	120 household segments distinguished - Modal shift options constraint based on urban area - Households use different hurdle rates in their investment decisions and face different capital constraints	Determined per household segment based on: urban area, activity (number of trips), household size
MARKAL-MACRO	- One central decision maker, optimization of total system costs - A higher hurdle rate (25 % instead of 10 %) is used for advanced and new technologies, in the residential sector these are all conservation measures, solar water heaters, appliances of class A⁺⁺ and A⁺, and in the transport sector these are all transport demand technologies	Change in overall demand in response to change in energy prices
IESA-sim	- Four adopter attitudes are distinguished: Innovators, early adopters, majority, laggards - Technologies are characterized by four aspects: costs, CO₂ emissions, complexity, social perceptions. Depending on the adopter attitude, actors assign different weights to these aspects - A weighed sum leads to an overall ranking of technologies being established per adopter attitude. The highest-ranking technology fulfilling a certain activity/demand is adopted. - No distinction is made between behavior in the residential and transport sector	Exogenous
ENSYSI	- Four adopter attitudes are distinguished: Innovators, early adopters, majority, laggards - Technologies are characterized by five aspects: costs, societal attitude, contribution towards sustainability targets, complexity, investment barrier. Depending on the adopter attitude, actors assign different weights to these aspects - A weighed sum leads to an overall ranking of technologies being established per adopter attitude. The highest-ranking technology fulfilling a certain activity/demand is adopted. - No distinction is made between behavior in the residential and transport sector	Exogenous
MUSE	- Agents can be assigned different decision objectives (e.g. maximizing comfort of technologies, maximizing efficiency, maximizing costs). - Different decision objectives can be combined in various ways, e.g. mean, weighed sum, determining an order of priority - When selecting technologies, agents follow different search rules, e.g. looking for technologies that fulfil a certain end-use or only considering technologies with a certain minimum market share. Search rules can also be combined and weighed	Demand is simulated in demand sectors and matched with supply sectors
BLUE	- Agents are distinguished by five adopter attitudes: innovators, early adopters, early majority, late majority, laggards - In the residential sector, agents make decisions over: heating system replacements, investment in microgeneration, investment in highly thermally efficient buildings - In the transport sector, agents make decisions over road transport choices - Investments per agent type depend on: hurdle rate, sensitivity to costs, intangible costs - Investments are determined by the Net Present Value of technologies in combination with the sensitivity to costs	Different demand elasticities per agent type (low, central, or high)
ENGAGE	- Households are divided by their income - Households buy generic goods that represent the goods that a household owns which contribute to energy consumption - Each year, income is first allocated to meeting energy requirements using the existing stock. Then, income is allocated to replacement or extension of stock - No explicit distinction is made between behavior in the residential and transport sector	Exogenous
CIMS	- One central decision maker, the model is focused on simulating technology market shares over time - Technologies are assigned discount rates and intangible costs based on discrete choice studies - An additional parameter determines the overall sensitivity to costs (e.g. if the value of the parameter is high, implying a high sensitivity to costs, only technologies with the lowest costs gain larger market shares) - No distinction is made between behavior in the residential and transport sector	Demand elasticities included
UK TIMES	Residential sector	Exogenous
	- Three types of households are distinguished based on the number of bedrooms (1–3, 4, 5+). - Technologies are divided into four heater types (gas, electric, heat pumps, solid fuel boilers), district heating technologies, conservation measures - At the end of technologies' lifetime, households choose heater types based on preferences indicated in a survey (i.e. per household groups, market shares of technologies derived from a survey are implemented) - Within a certain household group and per heater type, the model strives for cost-optimization	

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Table D.1 (continued)

Model name	Adoption decisions	Energy consumption
ESME	Transport sector • Cost-optimization approach • Endogenized modal shift: definition of overall passenger demand that can be met by different (competing) transport modes. So model can choose optimal configuration of modes • Transport modes are characterized by costs and travel time • Constraints: maximum modal shift potential from cars to non-car modes, rate of modal shift, overall travel time available to the population (average travel time budget for the population is calculated, the average speed of the final mix of modes cannot exceed this budget)	• Overall travel demand projected based on transport surveys
TIMES-IR & CA	Transport sector • Cost-optimization approach • Endogenized modal shift: definition of overall passenger demand (for long and short distances) that can be met by different (competing) transport modes. So model can choose optimal configuration of modes • Transport modes are characterized by costs and travel time • Constraints: overall travel time available to the population (average travel time budget for the population is calculated, the average speed of the final mix of modes cannot exceed this budget) • The model can invest in infrastructure, which leads to a reduction in travel time of public transport	• Exogenous travel demand
TIMES-DKEMS	• Overall cost optimization Transport sector • Elastic inland passenger modal shift • Per distance (extra short, short, medium, long), an elasticity of substitution is defined • Total demand is defined per distance, this total demand needs to be met after substitution • Constraint: Maximum shift potential	• Exogenous overall travel demand
MoCho TIMES	Transport sector • 24 groups of transport users distinguished based on: region of residential location, income level, type of residential location • Intangible costs are assigned to transport modes, differing per group of transport users • Constraints: overall travel time budget for all modes fulfilling overall demand, maximum modal shares by 2050 • The model can invest in new infrastructure	• Overall travel demand defined exogenously

Sectoral energy models

Model name	Adoption decisions	Energy consumption
HESTIA	Residential sector • “Activation moments” allow for building owners to invest in energy-related technologies of their building. Such moment include end of lifetime, renovation/moving, policy • Depending on these three aspects, for each activated apartment, one of three options is chosen: insulation, installation, nothing • Insulation and installation choices are determined using a probability function, weighing costs and benefits per insulation option. Options with the best cost-benefit relations have the highest chance of being chosen.	• Energy demand is determined based on dwelling characteristics
ABMoS-DK	Transport sector • Agents defined based on socio-economic characteristics and region, trip length, urbanization type, annual households income. • Transport modes characterized by costs and value of travel time • Utility of modes calculated per agent (influenced by characteristics of the mode and characteristics of the agents), agents choose mode with highest utility	• Travel demand defined per agent type based on transport survey

Data availability

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

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