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Review

Behavior matters: A systematic review of representing consumer mobility choices in energy models

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ABSTRACT

Consumer behavior is gaining increased attention for climate mitigation efforts, especially in the transportation sector. Thus, representing consumer mobility behavior in energy models is being strengthened to simulate realistic future vehicle and mode choices. This work focuses on two widespread concepts that modelers apply: (1) endogenous integration of mobility behavior in standalone energy models and (2) coupling complementary models to reflect behavioral dimensions through data exchange. This systematic review conducted four steps leading to 44 publications that apply such concepts to target consumer mobility behavior. First, we summarize the methodological approaches for each concept by describing the trends in implementing mobility behavior in models. Second, we discuss the challenges, limitations, and opportunities of both concepts to compare their values.

We find that endogenously representing mobility behavior in energy system models offers simplicity and complements their techno-economic perspective. However, this concept faces methodological limitations when translating behavioral attributes into monetary values. Model coupling can combine different perspectives on the transport and energy system but adds computational and methodological complexity. We conclude that stand-alone models are favorable for representing stylized parameters of consumer behavior, such as travel time and money budgets and electric charging infrastructure accessibility that can be generalized for consumer groups. Model coupling becomes superior when the impacts on the energy system of multifaceted mobility behaviors, such as preferences of individual consumers and actors of the transport system, are assessed in more detail. Nonetheless, both concepts should be viewed as complementary to overcome their limitations while merging their strengths.

1. Introduction

Computational energy models are often used to assess energy and climate change mitigation policies by evaluating technological, economic, political, environmental, and societal aspects [1,2]. Currently, no single modeling framework is capable of representing each of these aspects with a high degree of detail. Instead, several model frameworks exist with individual focus areas. Common model frameworks, comprehensively reviewed by Bhattacharyya and Timilsina [3] and Herbst et al. [4], are bottom-up and top-down Energy System Models (ESMs), Integrated Assessment Models (IAMs), and models reflecting socio-technical transitions [5]. ESMs usually comprise a detailed bottom-up techno-economic characterization of technologies [4]. They are used to provide long-term transition analyses on technology portfolios, energy demand projections, and greenhouse gas emissions [4]. However, they contain traditionally no or limited representation of

Abbreviations: ABM, Agent-Based Model; BEV, Battery Electric Vehicles; CES, Constant Elasticities of Substitution; CGE, Computable General Equilibrium; DEEM, Direct Energy and Emission Model; E3, Energy-Economic-Environment; ESM, Energy System Model; EV, Electric Vehicle; IAM, Integrated Assessment Model; LCEIM, Life Cycle and Environmental Impact Model; MaaS, Mobility as a Service; MARKAL, MARKet ALlocation model; MNL, Multinomial-logit; PHEV, Plugin Hybrid Electric Vehicles; PTT-MAM, Powertrain Technology Transition Market Agent Model; SD, System Dynamics; STEM, Swiss TIMES Energy systems Model; STET, Socio-Technical Energy Transition; TTB, Travel Time Budget; UKTCM, United Kingdom Transport Carbon Model.

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consumer behavior[1] due to their underlying pure cost-optimization approach that focuses on techno-economic characteristics and represents the population with one “mean representative decision-agent”[2] [6] [5–9]. IAMs combine the representation of the energy system with climate-, natural-, and human systems to determine pathways for energy consumption and greenhouse gas emissions [10,11]. One defining feature of global IAMs is their long-term time horizon (often until 2100), which is valuable for climate change analyses [12–15].

Models that reflect socio-technical transitions are Socio-Technical Energy Transition (STET) models, System Dynamics (SD) models, and Agent-Based Models (ABMs) [5,9,16]. Such models aim to integrate key elements from societal and technological transitions, such as actor heterogeneity, techno-economic details, and transition pathway dynamics [5,9,16]. Key differences of such models, compared to ESMs and IAMs, are the representation of non-linear dynamics of future transitions by feedback loops that cause endogenous changes in the system based on decisions of the actors [9]. Further, they can represent a high degree of heterogeneity with thousands of agents who can influence each other and make individual decisions based on multiple criteria [9,17,18].

Consumer choices and preferences are essential factors for the acceptance and market penetration of novel technologies and service demand paradigms in energy demand sectors [7,11,19,20]. As the focus for additional climate change mitigation measures is shifting from the energy supply sector towards energy demand sectors, the consideration of consumer choices and preferences in energy models is becoming increasingly important [11]. Accordingly, the representation of consumer behavior in energy demand sectors has gained increasing recognition within the energy modeling community [18,21–24]. Particularly for transportation, many research outlooks and recommendations emphasize the need and importance of improving behavioral realism in computational models and provide suggestions for achieving this [2,22,25–30]. Thus, it is essential to consider behavioral factors[3] besides providing zero-carbon technologies to decarbonize the transport sector [31,32].

Several trends have emerged to improve the representation of consumer behavioral realism in energy models [2]. Li et al. [9] provided a categorization for STET models and suggested how their key elements can be combined. Hirt et al. [5] showed that the linkage between models and socio-technical transition theories often aims to increase realism in models but mostly lacks in discussing concrete suggestions for increased model realism. Trutnevyte et al. [26] outlined strategies for linking existing models with insights from social sciences. Venturini et al. [22] reviewed measures for integrating behavioral aspects in Energy-Economic-Environment (E3) models. In follow-up work [33], Venturini outlined that model coupling enables to represent more spatio-temporal details and perform more comprehensive assessments than a standalone model. Krumm et al. [18] discuss that modeling teams of ABMs, ESMs, IAMs, and Computable General Equilibrium (CGE) models work on including behavioral aspects, but that each framework is limited in how well it can represent such aspects.

Studying the work described in the previous paragraph, we identified the need better to understand strengths and shortcomings among different modeling approaches. Therefore, we review two core concepts that many modelers have been working on in recent years. Such concepts are (1) the capturing of mobility behavior facets endogenously in energy models and (2) the improved representation of such facets by exchanging data across several models with complementary frameworks, i.e., model coupling/linking.[4]

We aim to answer the following research questions:

Q1: How are mobility behavior aspects implemented in energy models via the concepts of endogenous integration and model coupling?
Q2: What is the value of model coupling compared to endogenous integration?
Q3: What are the recommended strategies and potential trade-offs for considering mobility behavior in such models?

This systematic review adds value to the existing literature in four ways. Firstly, to the best of our knowledge, we provide the first comprehensive review about model coupling approaches that focus on enhancing the representation of mobility behavior. Secondly, this review generates insights into what kind of different model coupling approaches exist for including mobility behavior. Thirdly, this work goes beyond existing literature by highlighting and discussing the strengths and limitations of the two modeling concepts for reflecting mobility behavior. Fourthly, this paper provides straightforward, applicable suggestions for incorporating mobility behavior in energy models by each concept. This shall assist other researchers in their decision-making for the methodological concepts that best suit their needs for representing mobility behavior. Further, we determine research gaps and provide suggestions for improving the representation of mobility behavior in future research.

This review focuses on land-based passenger transport and methodological aspects. Specific model outputs, scenario analyses, or policy insights are beyond the scope of this paper. This review does not determine which factors influence consumer mobility behavior but investigates in-depth the state-of-the-art of how energy models reflect such behavioral aspects endogenously and via model coupling. We acknowledge that also other concepts exist for implementing mobility behavior in energy models.[5] However, they are not considered in this work, as the two covered concepts receive, in our view, currently most attention from the energy modeling community. Further, we acknowledge that the former concept was already reviewed by Venturini et al. [22], which is why we are building upon this review by including overarching measures and the latest state-of-the-art research. The rationale for including this concept in our review is that a good understanding of it is critical to put the need for the model coupling concept into perspective. Also, both concepts can be perceived as competing, which is relevant for our discussion and conclusion.

[1] Consumer behavior describes the decision-making of individuals with considering microeconomic realism [22,167]. Consumer mobility behavior refers, in the context of this paper, to behavioral aspects that are relevant to the mobility choices of consumers regarding vehicle purchase and modal choice as well as their usage of such technologies and services. Specifically, we focus on behavioral aspects related to land-based passenger transport consumer decision-making. In-line with the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [11], this includes aspects influencing the vehicle purchase behavior, willingness to adapt to new technologies/fuels, on-road fuel economy (e.g., driver behavior), eco-driving, driving behavior with new types of vehicles (e.g., recharging patterns and location of public recharging systems for electric vehicles), driving rebound effects, and vehicle choice-related rebound effects. In this paper, we refer mostly to consumer mobility behavior but also use mobility behavior synonymously.

[2] The concept of the “mean representative decision-agent” [6] describes the homogeneity in the decision-making in ESMs, which neglects the “heterogeneity, i.e., variation or differences between end-users” [6] in terms of their decision-making preferences.

[3] Mobility-related decision-making is largely influenced by consumer behavior. For instance, the availability of novel vehicle- and mode-technologies (e.g., micro-mobility solutions and high-speed transportation in reduced pressure tubes), new service concepts, such as car-sharing and Mobility as a Service (MaaS), and the emergence of autonomous driving vehicles can potentially change purchase- and usage decisions and mobility demand.

[4] The terms ‘model coupling’ and ‘model linking’ are used synonymously in this work.

[5] For instance, developing narratives/storylines that reflect societal developments, structurally changing current models, or developing entirely new models that can account for different relevant aspects for the energy system [18,26].

The paper is structured as follows: Section 2 presents the trends for enriching models with mobility behavior by using the concepts of mimicking mobility behavior endogenously in standalone energy models (Section 2.1) and applying different model coupling approaches (Section 2.2). Section 3 discusses the challenges, limitations, and opportunities of the presented concepts, identifies research gaps, and provides future research suggestions. Section 4 concludes this work. The Appendix includes the comprehensive review methodology applied for the literature search (Appendix A), details on each model coupling approach relevant to mobility behavior (Appendix B), an overview of exchanged parameters between models in such coupling approaches (Appendix C), and the advantages and challenges of model coupling in general (Appendix D).

2. Trends in implementing mobility behavior in models

Sections 2.1 and 2.2 present the research trends for enriching mobility behavior representation endogenously in energy models and by applying model coupling approaches, respectively.

2.1. Representing mobility behavior endogenously in standalone energy models

The endogenous integration of mobility behavior in standalone energy models started after Schäfer [21] reviewed the options and methods for including the following parameters of mobility behavior in Energy/Economy/Environment (E3) models: elastic transportation demand, endogenous modal choice models, choice of no (physical) travel, accounting for infrastructure capacity, and segmenting urban and intercity areas. Schäfer [21] concluded that including behavioral parameters in E3-models is feasible and important for holistic energy system analyses. Venturini et al. [22] comprehensively reviewed the following efforts for enabling such measures to model mobility behavior in ESMs directly. They classified the implementation of consumer mobility behavior into four categories: vehicle choice, modal choice, driving pattern, and new mobility trends. Based on our review, some methods can additionally be applied overarching across the four categories. The remaining section provides an orientation of the key measures for integrating mobility behavior in energy models along these four categories and overarching methods. Compared to Venturini et al. [22], this overview is extended with additional literature and the most recent developments to capture the complete picture, options within each category, as well as the state-of-the-art.

2.1.1. Vehicle choice

Translating insights from discrete choice models into feasible parameters is a common measure to include vehicle choice realism in ESMs [34–38]. In discrete choice models, individuals aim at maximizing their utility when making a choice. This allows going beyond the typically existing tangible costs in such models by considering intangible costs for aspects such as technology acceptance, car model availability, range anxiety, or charging/fueling infrastructure.

Disutility costs[6] are applied by some modelers to proxy behaviors by a discomfort, i.e., the monetization of intangible costs, encountered by a consumer when adopting a specific transport vehicle (or mode) [6,20]. The disutility method is commonly used for vehicles with novel drivetrains. Bunch et al. [20] represented consumer technology preferences in a TIMES ESM by integrating disutility costs for refueling inconvenience, range limitations, risk premiums, and brand and model diversity. This theoretical framework was tested in a case study with a more advanced ESM by Ramea et al. [39], who found that integrating disutility cost in ESM enablesto closely mimic the outputs of the vehicle choice model in the ESM. As this ESM could not dynamically adjust the disutility costs for the future time horizon based on the model's results in previous years, subsequent work [40] tackled this issue: the ESM was extended by an internal feedback mechanism that let it operate iteratively to induce some behavioral realism. After each iteration, the simulated vehicle sales and stock dynamically update some of the disutility cost terms, which are fed back to the model as inputs until the model output converges.

Constant Elasticities of Substitution (CES)[7] between input parameters of a utility function were applied in top-down CGE models [41,42]. In addition to the CES in such models, they improvised the behavioral dimension of vehicle choice by attributing fixed disutility costs to novel vehicle types to represent additional perceived barriers of consumers for adopting such vehicles [42]. To integrate CGE models in ESMs, hybrid modeling approaches or model coupling are necessary.

Hurdle rates[8] were implemented to represent mobility behavior for technologies that are new to consumers or not fully matured in the market yet [43]. The concept of hurdle rates has already earlier been used to mimic consumer behavior in other sectors of ESMs [44]. Regarding mobility behavior, hurdle rates can account for uncertainty, a higher investment risk, and the lack of knowledge from the consumer.

2.1.2. Modal choice

The modal choice reflects the consumer choice across different transport modes such as car, bus, tram, or train. Some ESMs enable modal shift endogenously in contrast to exogenous assumptions on modal shares.

Travel money budgets limit the total monetary budget of tangible costs for the consumer, typically following historically observed data [45]. For instance, Tattini et al. [46] applied a monetary travel budget by limiting the consumption of cost commodities perceived by the consumer depending on their income class. Thus, such monetary budgets steer modal shifts by ensuring that consumers do not spend more money on mobility than historically observed in their income class.

With a similar analogy, Travel Time Budgets (TTBs) are applied. The rationale for TTBs is that people spend a certain amount of time per day traveling [45]. This approach has been applied in models to stimulate shifts to faster transport modes when the income rises and therewith longer distances are covered within the same amount of time [47–52]. However, while research shows that the average TTB is constant, it varies by sociodemographic group, income, and congestion level, which we have not found to be reflected in standalone ESMs [45]. The TTB is further enriched with so-called “Travel Time Investment” [51] that aims to enable endogenous investments in infrastructure availability to increase their associated travel speed and, therefore, reduce the travel time of the corresponding mode [46,51–54].

Discrete choice models are frequently applied in transportation problems [55,56]. They can predict the modal choice probability based on travel costs and travel time [34–36,38]. Like the vehicle choice, the insights of such discrete choice models are translated into parameters relevant for modal choice in energy models.

CES is often applied to represent modal choice in a top-down framework where the CES values are typically estimated, as they cannot be quantified on directly observable data. The transport demand module of the PRIMES-TREMOVE model applies CES to allow modal choices based on trip-specific characteristics [57]. However, model validation of PRIMES-TEMOVE has shown that such elasticity

[6] “disutility costs link to the non-monetary preferences found to be influential in empirical studies (e.g., range anxiety, lack of refueling station availability, risk aversion […]” [6].

[7] “The CES utility function […] gives rise to homothetic preferences, which means that the ratio of goods demanded depends only on their relative prices, and not on the scale of production” [42].

[8] “Hurdle rates refer to the discount rates applied to the investment cost of new technologies which are meant to mimic hesitancy on the part of the purchaser to invest in a newer technology over an established technology.” [168]

Table 1
Distinction of standalone model improvements and model coupling approaches when input data come from other models.

Standalone model improvements	Model coupling	
	Soft-linking	Hard-linking
• Input data come from external sources (e.g., surveys or models) that the modelers cannot control.	• Modelers (or model consortia) can access and control the involved models: models are developed '*in-house*'.	
• No specific agreement for developing a shared coupling framework.	• Modelers agree on a coupling framework, common scope, and shared assumptions for the models.	
	• The user controls and evaluates data exchange between models [68].	• Computer programs handle the entire data exchange between models without any judgment or interference by the user [68].

Note. Standalone models often adopt data from external models (or databases) to which the modelers may not have access to exchange data systematically. In this context, standalone models are static, and data of the external models are usually extracted from reports or similar. On the contrary, in the context of this paper, model coupling/linking is characterized by modelers (or model consortia) having full access to the models to be coupled/linked so that interactive variables (data) can be consistently or systematically exchanged (one-way or two-way) for assessing a wide range of scenarios or sensitivities. In such a setup, the involved models are developed '*in-house'*, and the modelers of the different models interact with each other by agreeing on a coupling framework, common scope, and shared assumptions. Model coupling is further clarified via soft-coupling and hard-coupling depending on the computational approach. Also, linked models can apply a one-way or two-way exchange of variables (interactively).
It is noteworthy that several definitions in the literature distinguish model coupling mechanisms [68,70–73]. However, a clearly defined distinction from endogenous improvements of standalone models by using data from external models seems to be missing. For example, Kannan and Hirschberg [63] adopted in the Swiss TIMES Energy system Model (STEM) future mobility-demand trajectories from the ARE model [69]. However, STEM modelers did not have access to the ARE model, and therefore mobility demand in STEM was not systematically changed. Although this approach is similar to 'model coupling', it does not meet the criteria for 'model coupling' and is therefore not classified as such. Instead, it is classified as a standalone model enhancement. We acknowledge that it is not always evident in the existing literature to identify which of such two categories a modeling approach belongs to.

substitution values are small, which is in line with empirical studies that found modal shifts to be relatively inflexible [57]. Others represent shifts between similar transport modes by a CES function containing approximated fuel efficiency values and the substitution elasticity for how replaceable one mode is by another mode [58]. Waisman et al. [50] apply CES to describe the relationship between per-capita income and motorization rate, i.e., car access for different households. They, therefore, determine the modal shift rate of consumers towards cars or other transport modes depending on their level of income. Karplus et al. [42] enrich their CGE framework with an income elasticity that considers the per-capita income to assess the traveled vehicle kilometer, which leads to modal shift when, for instance, fuel prices are changing.

Different transport modes are characterized by their potential distance ranges [52,59]. Thus, for each trip distance, the modal shift is limited to such transport modes that can meet demands with the corresponding distance. While this measure requires detailed input data on trip-level, it prevents a model, for example, from utilizing a metro to fulfill the demand of very long trips (>50 km) or to use a train for very short trips (<5 km).

2.1.3. Driving patterns

Driving patterns refer to the on-road and off-road times of mobility services, such as car or bus, and the distances traveled within such times of a day (driving profiles). They relate to the speed profile of vehicles and modes, depending on traffic conditions and available infrastructure, and can be associated with aspects such as eco-driving.[9] Thus, driving patterns can distinguish, for instance, by trips in different regions (urban and non-urban areas), trips with different distances, and trips at different times (peak- and off-peak travel times), and they have a direct influence on the fuel efficiency, energy consumption, and produced CO_2 emissions [60–62].

Salvucci et al. [52] adopted a methodology that was previously introduced by Daly et al. [49] and refined by Tattini et al. [59] for distinguishing different categories of trip demands by their distances (extra-short, short, medium, and long-distance) in a TIMES model. Driving patterns are for each transport mode considered by differentiating the travel demand that is being traveled within each trip distance category, based on the share of km within such categories found in a mobility survey [59]. While we outlined before the aspect of travel time included in these models, it is noteworthy that each trip distance range considers several driving pattern aspects, such as different travel speeds, infrastructure availability, and traffic conditions, which all influence the travel time [49]. However, such aspects of driving patterns connected to the different trip distance ranges are represented on an annual level. Thus, the time granularity in these approaches does not allow to reflect driving patterns in its traditional sense for representing the on-road and off-road times, speed, and traveled distances within a day.

In ESMs with a higher time resolution, driving patterns can be represented on an hourly level, as performed by Kannan and Hirschberg [63]. By including the time of driving, they proxy the on-road and off-road times of cars. However, they have not represented further specifications for driving patterns, such as differing individual driving patterns by trip distance, trip region, or the related lower/higher fuel efficiencies based on the vehicle speed in hours with peak/off-peak travel demands. In contrast, in PRIMES-TREMOVE [57], trips distinguish by geographical area (urban metropolitan, other urban areas, inter-urban motorways, and inter-urban other roads), purpose (non-working, commuting, and business trips), and time (peak and off-peak). Such trip types enable to represent travel habits of different representative consumers per region and trip.

2.1.4. New mobility trends

New mobility trends refer to novel aspects such as carpooling, car sharing, mobility as a service, autonomous vehicles, and the choice of no physical traveling due to teleworking or similar [21].

So far, measures representing new mobility trends or mobility business models have received low attention in energy models [28,35]. However, efforts for representing novel mobility trends in models perceive an increased interest in the ESM community [28] and in broader fields of social sciences that work on quantifying the impacts of such new mobility trends on mobility decisions of consumers, which can create data that can be beneficial for integrating such trends in energy models [64,65].

2.1.5. Overarching methods across the four categories

Some measures allow integrating mobility behavior in ESMs across multiple outlined categories. One overarching aspect that is frequently being applied is the extension from one homogeneous consumer towards heterogeneous consumer segments: this allows recognizing differing socio-economic backgrounds within the population relevant for mobility choices, such as income level and driving frequency, and enables policy analyses of tailored measures for different groups of the population [6,20,37,39,46,66,67]. Consumer heterogeneity improves models in each of the outlined four categories by applying it in combination with

[9] "Eco-driving reduces fuel consumption through more efficient driving style, reducing speeds, proper engine maintenance, maintaining optimal tire pressure, and reducing unnecessary loads." [169]

Table 2
Overview of reviewed model coupling approaches that include aspects of mobility behavior.

Model 1			Model 2			Further models	Coupling framework				
Name	Framework	Scope	Name	Framework	Scope	Name (scope)	Soft-link vs. hard-link	Data iterations	Time horizon	Geographical coverage	Source
MED	ESM (optimization)	Systemic energy perspective	UKTCM	Transport model	Vehicle choice	-	Soft-link	No	2050	United Kingdom	Anable et al. (2012) [71]
TIMES-DKMS	ESM (optimization)	Systemic energy perspective	DCSM	Transport model	Vehicle choice and -stock	-	Soft-link	Yes, until convergence	2050	Denmark	Tattini et al. (2018) [72]
Irish TIMES	ESM (optimization)	Systemic energy perspective	Car Stock model	Transport model	Vehicle choice and -stock	-	Soft-link	Not specified	2035	Ireland	H. Daly et al. (2011) [73]
Irish TIMES	ESM (optimization)	Systemic energy perspective	CarSTOCK	Transport model	Vehicle choice and -stock	CIMS Market share algorithm (hybrid energy-economy framework)	Soft-link	No	2050	Ireland	Mulholland et al. (2017) [74,75]
REMix	ESM (optimization)	Systemic energy perspective	VECTOR21	Transport model (hybrid of agent-based and discrete choice market penetration)	Vehicle fleet model	VencoPy (EV-charging model), CURRENT (EV-charging model)	Soft-link	No	2030	Germany	Wulff et al. (2020) [76]
TIMES-DK	ESM (optimization)	Systemic energy perspective	ABMoS-DK	Transport model (agent-based)	Modal choice	-	Soft-link	Yes, until convergence	-	Denmark	Tattini et al. (2018) [77,78]
IMAGE-TIMER	SD energy model (TIMER) within an IAM (IMAGE)	Systemic energy perspective	TRAVEL	Transport model (based on MNL)	Modal- and vehicle choice	-	Hard-link / “integrative”	No	2100	Global	Girod et al. (2012) [34]
MARKAL	ESM (optimization)	Systemic energy perspective	Modal Split Model	Transport model (myopic foresight)	Modal choice	MIT EPPA model (emission model with myopic foresight)	Soft-link	Yes, until convergence (calibration stage)	2030	Global	Schäfer & Jacoby (2005) [79]
JRC-EU-TIMES	ESM (optimization)	Systemic energy perspective	PTT-MAM	SD² simulation model	Representing systemic agents in the car market	Dione (fleet impact tool), EV-charge (EV-charging model), GIS EV Infra (GIS-based charging infrastructure allocation tool)	Soft-link	Not specified	-	EU28	Thiel et al. (2016) [80]
JRC-EU-TIMES	ESM (optimization)	Systemic energy perspective	PTT-MAM	SD simulation model	Representing systemic agents in the car market	-	Soft-link	Yes, until convergence	2050	EU28, Switzerland, Norway, and Iceland	Blanco et al. (2019) [81]
TE3	SD model	Energy demand and greenhouse gas emissions of cars	PTT-MAM	SD simulation model	Representing systemic agents in the car market	-	Soft-link	Yes, until convergence	2030	Europe, China, India, Japan, and USA	Gómez Vilchez & Thiel (2020) [82]
TIMES-FR	ESM (optimization)	Systemic energy perspective	Lifestyle model	Input-output model	Transport demand	Metanoia (macroeconomic input-output model)	Soft-link	No	2072	France	Millot et al. (2018) [83]
REMix	ESM (optimization)	Systemic energy perspective	CURRENT	Transport model	EV charging	-	Soft-link	No	2030	Germany	Steck et al. (2019) [84]
TDM	Transport model	Transport Demand	VSM	Transport model	Vehicle choice and -stock	DEEM (Direct Energy and Emission Model), LCEIM (life cycle model)	Hard-link / “integrative”	No	2050	United Kingdom	Brand et al. (2012) [37]
Socio-economic consumer choice model	Transport model (based on revealed preference)	Vehicle and modal choice	CarSTOCK	Transport model	Vehicle choice and -stock	-	Hard-link	No	2050	Denmark and Ireland	Mulholland et al. (2018) [85]
Time Budget Model	Transport model	Transport Demand	Vehicle park model	Transport model	Vehicle choice and -stock	- (CGE model), - (Freight demand model), - (fuel demand model)	Soft-link	Not specified	2050	South Africa	Merven et al. (2012) [86]
AIM/Transport	Transport model (based on MNL)	Transport Demand	AIM/CGE	CGE model	Top-down economic perspective	-	Soft-link	No	2100	Global	Mittal et al. (2017) [87]

Note. The color coding refers to the combination of the model types that have been coupled following the four groups outlined in Section 2.2. Blue: Vehicle choice transport model and ESM; green: Modal choice transport model and energy (system) model; yellow: SD model and ESM (or another SD model); grey: other model combinations.
[1]MNL: Multinomial-logit equations used to reflect discrete choice.
[2]SD: System Dynamics.

the corresponding measures. For instance, consumer segments assigned with different income levels can be assigned with respective travel money budgets, which could lead to distinguishing modal choice and vehicle purchase preferences across the segments with implications for mobility- and energy demands, and the energy supply mix. Ramea et al. [39] achieved an even higher level of heterogeneity within each consumer segment. They calculated for each consumer segment a probability distribution that represents non-measurable differences in the preference of consumers as error terms. Each consumer within a segment, so-called ‘clones’, falls somewhere into this probability distribution. Accordingly, an additional cost term has been implemented for each clone within that segment.

2.2. Model coupling advancements for representing mobility behavior

Model coupling describes data exchange between two or more models that complement their individual framework, scope, focus area, or context. Across the involved models, computed output data of one

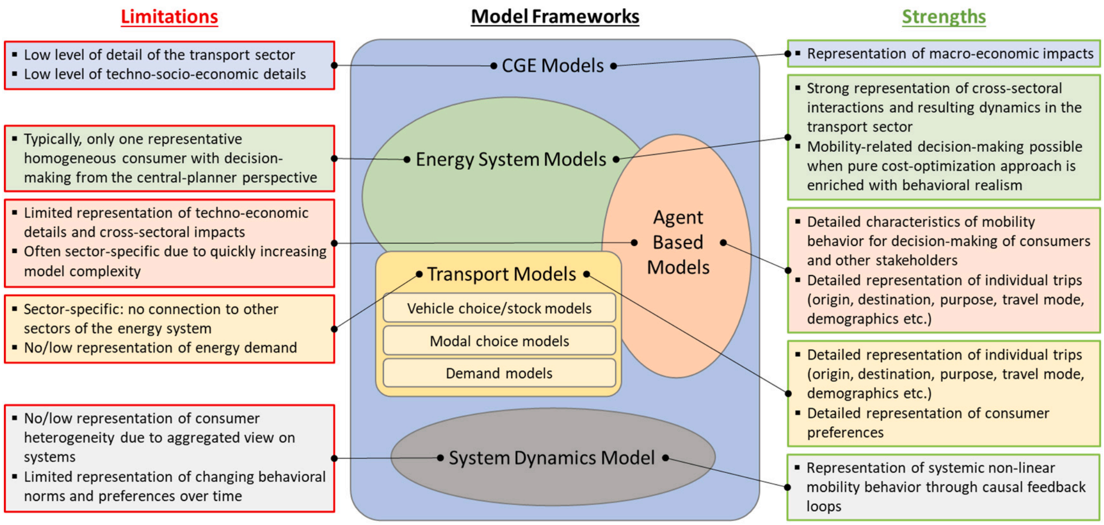

Fig. 1. Overview of existing model frameworks applied in the analyzed model coupling approaches. Different model frameworks and their overlaps with other frameworks are visualized. The limitations (left) and strengths (right) for representing mobility behavior are outlined for each framework.
Adapted from [70].

model serve as input for the other model. Data exchange can be in one direction or back and forth. In the latter case, data can be exchanged once or in an iterative manner to consider feedback loops between the models. The terms 'model coupling' and 'model linking' are used synonymously in this work. It is essential to distinguish between model coupling and improvements of standalone models, which adopt data from external models/databases (see Table 1).

Multiple definitions exist to describe the methodological linkage mechanism. We follow the definitions of Wene [68], who defined '*soft-linking*' as a method where the data exchange between models is controlled and evaluated by the user. In contrast, '*hard-linking*' involves computer programs that handle the entire data exchange between models without any judgment or interference by the user (see Table 1). It is noteworthy that in some of the reviewed literature, it remains unclear whether models are hard-linked or integrated into one model framework. Böhringer and Rutherford [69] distinguish between three categories: (1) coupling existing large-scale models, (2) complementing one model with a reduced form of the other model, and (3) combining characteristics of the models. We do not follow the definition of these latter three categories because they typically refer to coupling top-down and bottom-up models, which is not the focus of this review.

Based on insights from the reviewed literature, mobility consumer behavioral aspects in model coupling refer to the determined use of models that focus on vehicle choice- or vehicle stock, vehicle charging, modal choice, system dynamics, mobility demand, travel time, and similar.

Table 2 presents an overview of the models and frameworks of each coupling approach identified through the applied review methodology (see Appendix A), i.e., approaches that focus on the transport sector and consider aspects of consumer behavior. While this section provides an overview of such model coupling approaches, an in-depth description of each approach, the data exchanged between the models, and the order in which the models are applied is provided in Appendix B. Concerning the individual models used within the analyzed model coupling approaches, Fig. 1 provides an overview of such model frameworks. Table 3 synthesizes for each coupling approach the research objectives, the qualitative purpose of the model coupling, its methodological rationale, and the methodological limitations. Appendix C shows which parameters are exchanged between the models in each coupling approach.

There are several ways to group the reviewed coupling approaches, such as by their goals, coupling mechanisms, exchanged data, or data iteration approach. Since we aim to understand how model coupling enables energy models to consider behavioral aspects, we decided to group and summarize them in this section by their coupling mechanism, i.e., scope and framework of the coupled models (as shown in four color shades in the tables). This grouping helps identify which model types have been combined in the literature. In the discussion (Section 3), we translate this grouping with the help of Table 3 towards goal-oriented practical modeling insights.

2.2.1. *Vehicle choice transport model and ESM*

Linking a vehicle choice transport model with an ESM enables to represent consumer behavior of vehicle purchase decision-making.

Daly et al. [73] soft-linked the Irish TIMES ESM [88] and the Car Stock Model [89]. The models exchanged data in both directions to utilize their combined strengths, i.e., the interaction with other sectors in the ESM and the broad choice palette for vehicle technologies in the vehicle choice model. Building upon such developments, Mulholland et al. [74,75] enrich this model coupling with the additional CIMS market share algorithm [90], representing heterogeneity and varying consumer preferences for new technologies. Tattini et al. [72] went one step further by combining models that represent behavioral realism towards car choice and modal choice. The simulated car stock of the holistic and purely techno-economic TIMES-DKMS model [59] is in an iterative manner verified regarding its technical feasibility against the behaviorally-detailed DCSM model [72]. If the models are in disagreement, a capacity constraint is added to TIMES-DKMS to let it adhere to the car share projections of DCSM. Another approach develops lifestyle storylines that reflect societal preferences and lead to different travel pattern projections [71]. The impacts of such lifestyle storylines on vehicle choice, usage, and ownership are simulated in the United Kingdom Transport Carbon Model (UKTCM) [37,91]. The outputs of UKTCM serve as input to the MED model [92]. This entire approach analyses the combined effects of behavioral change and technological change to reach emission reduction targets [71]. Wulff et al. [76] linked three models in sequential order to find impacts from user behavior for EV charging on the energy system. By substituting two different EV charging models [93,94] with each other in their combined approach with a vehicle fleet model [95] and an ESM [96], they compared the influences of a more or less flexible electric charging infrastructure and charging behavior.

2.2.2. *Modal choice transport model and energy (system) model*

Combining a modal choice transport model with an energy (system)

Table 3
Research objective, qualitative purpose, methodological rationale, and limitations of the reviewed model coupling approaches.

Overall research objective	Qualitative purpose of the model coupling (what does the coupling achieve?)	Methodological rationale for the model coupling (what is the methodological reason for applying the coupling?)	Methodological limitations stated for the model coupling approach	Source
• Highlight the role of policy to positively influence how society is developing. • Investigate the role of lifestyle changes that focus on transport activity for achieving climate goals.	• Explore implications for the energy system when a substantial shift of societal lifestyles and preferences occurs. • Apply systematic comparison of scenarios to examine key uncertainties.	• Calculate impacts of lifestyle changes on mobility-related aspects within a sectoral model and find the associated transport energy service demands in a systemic model.	• The scenarios assume strong shifts in travel activities, preferences, and price signals. Those would lead to significant systemic implications, e.g., for the economy and society, that have not been addressed.	Anable et al. (2012) [71]
• Calculate the impacts of several transport policies on reducing greenhouse gas emissions.	• Provide more realistic car choice preferences of consumers to study decarbonization potentials in an ESM.	• Employ the respective strengths of each model in a combined approach: the holistic energy system approach (TIMES-DKMS) and the behaviorally-detailed car consumer choices (DCSM)	-	Tattini et al. (2018) [72]
• Focus on developing and testing a soft-linking coupling approach.	• Align complementary models with different layers that can be analyzed	• Create results that depend on system-wide energy targets for a minimalistic technology selection and specific technology measures for more disaggregated modeling.	-	H. Daly et al. (2011) [73]
• Bridge the gap between modeling and policy analysis in transportation by bringing attention to “policy roadmaps” and “enabling measures” [75].	• Provide a comprehensive description for decarbonizing the private car sector that considers potential technology pathways and the need of different technologies for more/fewer policies stimulations.	• Combine the strengths of an optimization model for sketching potential technology pathways, a simulation model for indicating policy roadmap, and analytical approaches to analyze the critical policy measures. With this combination, they go “beyond the traditional multi-model approach” [75].	-	Mulholl and et al. (2017) [74,75]
• Reflect the flexibility in the energy system for charging EVs by considering user behavior concerning their decisions on where, when, and to what extent they charge their EVs in the future.	• Evaluate how the representation of the charging process for BEVs influences the results of energy system optimization.	• The charging behavior of consumers will impact the role of EVs in the electricity system. Thus, a modeling approach that combines four models that focus on vehicle purchase choices, BEV charging behavior, and the energy system is developed to represent consumer charging behavior and evaluate the effect of such decisions on the energy system.	• Sensitivity of consumers towards electricity prices for charging EVs is not time-dependent • Static vehicle adoption pathways • Further limitations are mentioned for the individual models (e.g., simplified charging behavior assumptions, current driving patterns remain unchanged in the future)	Wulff et al. (2020) [76]
• Improve the depiction of human behavior in the transportation sector and assess the effectiveness of policy measures for modal shifts in the future energy system.	• Assess impacts of increased behavioral realism for modal choice on cost-optimal technology investments and development of other energy sectors.	• Apply policy measures in the behavior-oriented ABM to calculate modal demands, which are used by the systemic ESM to find the suitable cost-optimal technology investments, impacts on the entire energy system, and fuel prices, which are fed back to the ABM.	• The ESM is applied without environmental targets to focus on the impacts of the modal shifts provided from the ABM and avoid discrepancies due to other constraints.	Tattini et al. (2018) [77,78]
• Explore whether and how stringent CO_2 emission reductions could be achieved in the global passenger transport sector.	• Assess with TRAVEL detailed pathways for transport modes and technologies within the scope of the less detailed IMAGE-TMER model.	• The global transport model TRAVEL can determine detailed modal shares and vehicle fleet compositions. It receives input data on population, income, and energy prices from the IMAGE-TIMER energy model in which it is integrated.	-	Girod et al. (2012) [34]
• Explore the integration of specific automobile technologies into the vehicle market in a cross-sectoral and cross-regional assessment of greenhouse gas emissions constraints	• Find a specific set of transportation technologies that is consistent with a certain general equilibrium climate policy simulation	• Combine the analysis of technological change, economic growth, and greenhouse gas emissions from the EPPA model with detailed insights from the MARKAL model on technologies that can be applied to satisfy the economy’s transportation demands. • A third model, which uses myopic foresight and focuses on modal splits, is applied to connect the different levels of aggregation in both models.	• It is challenging to achieve consistency between the models because they are based on different data sets and analytical structures. • Careful analysis of consumer behavior and technology change impacts on other sectors than transport is neglected. • Substitution elasticities in the EPPA model needed essential tightening to attain a transport sector representation consistent with the ESM. • Aspects of substitution are implicit in the elasticity of the CGE model but are not accordingly represented in the ESM.	Schäfer & Jacoby (2005) [79]
• Assess if the European goals of vehicle deployment can be reached for EVs.	• Examine a broad set of aspects relevant for policy support regarding non-conventionally fueled cars, particularly EVs.	The combined approach of the integrated electro-mobility modeling platform allows to… • …examine relationships across users, infrastructure providers, policy options, and vehicle manufacturers • …evaluate options to decarbonize the road transportation system and assess the impacts of such options for the energy supply sector	-	Thiel et al. (2016) [80]
• Explore approaches for overcoming the high costs of fuel cell EVs and promoting their market penetration. • Provide improved policy recommendations.	• Examine the impacts of soft-linking on the model results compared to the outputs of the standalone models • Quantify the impact of various subsidies and policies on the uptake of fuel cell EVs and the cost efficiency of such policies.	• Both complementary modeling frameworks enrich each other by combining the perspectives of a systemic ESM and a detailed passenger transport simulation model. This improves the result quality and provides better policy recommendations. • The coupling enables to cover several aspects in the perspective of the entire energy system (e.g., feedbacks from updated demands on prices, endogenous cost developments, and consideration of several market players) • Two different coupling approaches are tested.	Coupling approach that uses only the costs from the SD simulation model: • the behavioral aspects of this model are not fully captured. • Additional constraints are necessary in the ESM to avoid non-disruptive scenarios.	Blanco et al. (2019) [81]
• Shed light on the possible deployment of EVs on a broad international scale.	• Investigate the potential future deployment of BEV and PHEV powertrains in important electromobility markets (India, Europe, China, Norway, Japan, and the United States)	• A soft-linking approach was selected because the different structure and size of both models made it not possible to integrate them into each other. This soft-link served as an exploration of the first step towards a potential model integration in future work. • The model coupling allows combining the high level of CO_2 emission targets from governments and strategies of vehicle manufacturers in the PTT-MAM model, with a consumer segmentation with emphasis on energy demand and emission dynamics in the TE3 model.	• Limited assessment of real-world policy measures • No representation of supply-side constraints for meeting the battery demand • The market penetration of freight vehicles and electric buses (outside the EU and China) was not considered, leading to a missing reflection of their impact on decreasing costs for EV components and their infrastructure.	Gómez Vilchez & Thiel (2020) [82]
• Assess the options for France to reach the targets of the Paris Agreement.	• Explore the long-term effects of lifestyles on the energy system.	• The three applied models each represent a dimension of the entire system, i.e., economy, technology, and lifestyle. The combined modeling approach reflects the interdependencies between these dimensions and assesses the impacts of lifestyles on the energy system.	-	Millot et al. (2018) [83]
• Examine the effect of price sensitivity on greenhouse gas	• Establish feedback between the energy supply and energy demand due to EV	• The linkage combines information about energy supply and electricity demand patterns of consumers. With	-	Steck et al.

emissions for the charging demand of EVs.	charging to properly assess the emission reductions that can be achieved using EVs.	this approach, the feedback loop of price sensitivity for vehicle charging of consumers impacts greenhouse gas emissions.		(2019) [84]
• Fill the gap for "integrated scenario modelling capability for research and practice that is appropriate for modelling the wide range of policies needed to decarbonise the transport system." [37]	• Introduce a model framework that captures carbon emissions from the entire life cycle in a policy-relevant context for the transport sector • Close the gap between scenario models with a long-term time horizon and forecasting models with a short-term time horizon.	• The newly developed UKTCM integrates four linked models to cover energy, transport, greenhouse gas emissions, and environmental impacts in a joint approach. • It considers policy influences and socio-economic impacts for reducing energy demand, greenhouse gas emissions of the entire lifecycle, and external costs.	• Model framework cannot endogenously represent the specifics of "smarter choices" [36] policies with a high level of detail. • Minor representation of other sectors than transportation	Brand et al. (2012) [37]
• Identify the impact of removing tax incentives for BEVs and PHEVs. • Examine the cost and efficacy of including additional government-level initiatives to stimulate the purchase of BEVs and PHEVs.	• Reflect a higher accuracy of consumer choice representation in models to avoid oversimplified representations. • Capture differing preferences of heterogeneous consumer segments and the hurdles for the market penetration of non-conventional vehicles at such consumers.	• Combination of a non-linear socio-economic consumer choice transport model, representing behavioral attributes via intangible costs based on consumers' revealed preferences for publicly available empirical data, and a sectoral car stock simulation model. • The latter model uses market shares of the previous model to find overall effects of policies on vehicle stock and activity, energy consumption, and CO_2 emissions.	• Non-private vehicles, such as taxis or business cars, are neglected • Limited number of behavioral parameters can be considered in the modeling framework	Mulholl and et al. (2018) [85]
• Provide insights on future trends for passenger and freight transportation demands, vehicle stock, and the related energy demand and CO_2 emissions.	• Combine multiple dimensions of the transport sector to develop qualitative future projections for mobility and energy demand and assess the necessary infrastructure.	• The interaction of a suite of five models reflects different angles of the transport system (vehicle stock, travel demand based on time budget, household income, freight demand, and fuel demand). This makes it possible to generate future energy demand projections. • This model combination provides a "versatility of the methodology" [86].	• Limited representation of vehicle usage • Enriching the vehicle model with energy or fuel demand calculation would enable the assessment of fuel consumption and necessary infrastructure investments by province. • Car ownership representation and passenger mobility demand could be improved by enriching the vehicle model with a separate higher-income consumer segment and a link between household income and car ownership.	Merven et al. (2012) [86]
• Find factors that impact the dynamics of global travel demands, modal shares, and the respective energy consumption and CO_2 emissions.	• Achieve more dynamic and disaggregated insights on the transport sector than the standalone AIM/CGE. • Assess the potential of induced travel behavior changes for carbon emission reductions	• The AIM/CGE model provides high-level systemic inputs to the transport model. The latter builds, in turn, on MNL-type equations for determining the technology and modal choice of consumers in the transport model. • The linked transport model allows to consider several behavioral aspects relevant to quantifying the transport sector's climate change mitigation potential.	• Due to missing feedback from the transport model to the AIM/CGE model, effects from the behavior-oriented dynamics on other sectors of the energy system cannot be examined. • No representation of availability and costs of transport infrastructure in the transport model. • No heterogeneous consumers	Mittal et al. (2017) [87]

Note. The color coding refers to the combination of the model types that have been coupled following the four groups outlined in Section 2.2. Blue: Vehicle choice transport model and ESM; green: Modal choice transport model and energy (system) model; yellow: SD model and ESM (or another SD model); grey: other model combinations.

model allows an improved representation of modal shift, which is essential for achieving climate targets.

Schäfer and Jacoby [79] performed a model coupling approach within this group by combining a MARKet ALlocation (MARKAL) model [97] with a CGE model for emission- and policy analyses (EPPA) [98] and two transport-specific modal split models for passenger and freight transport [45], respectively. Their approach considers consumer behavior by accounting in the dedicated modal split model for a daily TTB combined with travel speeds of different transportation modes. Later, Girod et al. [34] integrated the global passenger transport model TRAVEL into the TIMER energy model, which is part of the IMAGE IAM [99] and feeds TRAVEL with data on population, income, and energy prices. In TRAVEL, two behavioral parameters serve as key drivers for modal choice by representing empirical observations regarding a constant travel income budget and a daily TTB. A coupling approach that takes many behavioral aspects other than travel income and TTB into account has recently been developed by Tattini [77] and Tattini et al. [78], who developed an iterative soft-link between an ESM [100] and an agent-based modal shift model [101]. In this approach, the latter model simulates transport mode choices by taking travel behavior insights from a travel survey into account, while the ESM allows finding the impact of such decisions on a whole energy system perspective.

2.2.3. SD model and ESM (or another SD model)

Another identified group to consider mobility behavior through model coupling is combining a System Dynamics (SD) model with an ESM or another SD model. This combination allows broadening the scope from consumer-focused analyses towards taking the different transport market players into account. The Powertrain Technology Transition Market Agent Model (PTT-MAM) [102,103] is used in each of the three approaches. PTT-MAM is an SD behavior-based ABM representing four stakeholders within the EU transport market, i.e., users, authorities, infrastructure providers, and manufacturers.

Thiel et al. [80] outline a suite of five models [102–107] and state that "the models are soft-linked" [80]. Unfortunately, they do not explain the respective coupling methodology. However, the model most relevant for mobility behavior, PTT-MAM [102,103], has been applied in more coupling approaches in follow-up works: Blanco et al. [81] soft-link PTT-MAM with a multi-regional EU energy systems optimization model (JRC-EU-TIMES) [106], aiming to provide improved policy recommendations by combining the complementary strengths of each model. They tested two different approaches for data feedback from PTT-MAM to JRC-EU-TIMES. An improved mobility behavior was induced in the ESM by overwriting the powertrain market shares in the ESM with the behaviorally more realistic outputs from the PTT-MAM. Gómez Vilchez and Thiel [82] shed light on the possible deployment of EVs on a broad international scale by soft-linking the PTT-MAM with a global SD model [108] in an iterative manner until convergence was reached after a couple of iterations.

2.2.4. Other model combinations

Beyond the three groups summarized above, some model coupling combinations have been found that do not fit into those groups.

Two of the coupling approaches within this group apply an ESM. Millot et al. [83] use a soft-linking method to combine a statistical lifestyle model [109], a macroeconomic input-output model [110], and an ESM [111]. Human behavior from national surveys regarding household budgets, transport and journeys, housing, and a population census is represented via the lifestyle model. This approach allows testing the impacts of lifestyle dimensions, such as mobility practices and leisure travel preferences, on the energy mix and emissions. However, it does not consider any feedback, such as the impact of a carbon tax or changed fuel price on the consumer reaction. Steck et al. [84] do also not consider feedback loops when they soft-link an ESM [96] to a charging model [94]. They represent the dynamic charging demand of EVs by accounting for the decision algorithm of consumers, which is based on market mechanisms and charging preferences. Such charging behaviors are based on a real-world vehicle diary of Plugin Hybrid Electric Vehicles (PHEVs) and Battery Electric Vehicles (BEVs).

The remaining coupling approaches in this group do not apply an

ESM. Brand et al. [37] developed the UKTCM, which combines four hard-linked models [91]. An integrated feedback loop allows considering changing consumer preferences, income, and influences on vehicle purchase decisions. The exogenously defined scenarios that are simulated can describe changing attitudes and societal factors. Mulholland et al. [85] aim to find effects of financial stimuli for purchasing BEVs and PHEVs by hard-linking a socio-economic consumer choice model with two CarSTOCK models [89] for Denmark and Ireland, respectively. The former model covers the private transport sector in a non-linear fashion and represents 18 heterogeneous consumer segments. It combines tangible costs for the consumer with monetized intangible costs, such as range anxiety, car model availability, refueling infrastructure, and risk-related disutility. The intangible costs are based on empirical data of consumer preferences. Merven et al. [86] also aim to provide insights into the future vehicle stock and related energy demand by soft-linking five transport-related models [86,112,113]. Three of such models consider behavioral aspects (annual mileage and age of vehicles; daily TTB of 1.1 h per person; speeds transport modes; transport mode affordability based on three consumer income groups). Unfortunately, Merven et al. [86] neither outline which data are exchanged across the models nor the order in which the models are applied. Mittal et al. [87] soft-link the global transport demand model AIM/Transport [114] that represents technology- and modal preferences of consumers with the global AIM/CGE model [115,116] that applies MNL-type equations to reflect travel behavior. This coupling aims to find factors impacting global travel demands, modal shares, and respective energy consumptions. Most of the factors examined in this study relate to mobility behavior, such as travel time, preferences for transport modes, socio-economic macro-developments, the occupancy rate of a car related to the per capita income, and environmental concerns. Data were only transferred from AIM/CGE to AIM/Transport without a feedback loop.

3. Discussion: challenges, limitations, and opportunities for representing mobility behavior

The last years brought noteworthy improvements for representing consumer mobility behavior in computational energy models. Such improvements gain increasing recognition in the modeling community, as consumer behavior strongly affects the potential uptake of novel vehicle-drivetrains in the real world. However, such efforts come with generic challenges, such as reflecting the highly nuanced impacts on decision-making behavior in feasible terms in computer models and selecting the correct model type for answering different research questions [7].

This review reasons that well-designed model coupling approaches can provide additional benefits compared to the endogenous integration of behavioral measures in an ESM. Historically, modelers of ESMs tried to expand the degree of detail in many sectors of the energy system to the same degree. Recent efforts for adding aspects of mobility behavior endogenously in ESMs have shown improvements but also led to increased complexity that is becoming less manageable. Moreover, the cost-optimizing scope of most single ESMs leads to limitations when representing mobility behavior. Such limitations of standalone models can be overcome by model coupling. The latter lets each model remain a clear focus on its key area. At the same time, it provides a wider variety of insights from combining the complementary centers of attention of each model. Thus, model coupling prevents models from getting less computationally heavy and prevents individual models from becoming very large and complex. Therefore, applying well-designed linked models allows pushing the individual model limitations and boundaries by combining their strengths and extending the scope of analysis. Therewith, coupling enables considering more facetted parts of mobility behavior.

In the following, we discuss such aspects in detail for the advancements made by integrating behavioral aspects endogenously in standalone ESMs (Section 3.1) as well as by considering mobility behavior through model coupling of different model types (Section 3.2). In Section 3.3, we discuss the value of the latter concept compared to the former concept. Recommendations for future research are provided in Section 3.4.

3.1. Standalone ESMs

Mobility-related decisions of consumers reflect, to some extent, economically rational choices. Still, the decisions are also influenced by behavioral aspects that deviate from being purely explainable with economic rationality and, especially, cost-minimizing approaches that many ESMs follow. Behavioral aspects represent alternative rationalities of individual consumers, representing consumer preferences, which are often referred to as "*bounded rationality*"[10] [117,118]. Quantitatively assessing such aspects is challenging. Further, they show a high level of heterogeneity, which makes it generally challenging to represent such consumer behaviors in ESMs.

Despite such challenges, many approaches have been implemented and tested in standalone ESMs to induce mobility behavior endogenously. Most research integrates vehicle choice, modal choice, and overarching methods, such as heterogeneous consumer segments, in ESMs. Driving patterns and new mobility trends have received low attention in ESMs. Still, increased attention towards such aspects would be beneficial because of their potential significant impacts on future consumer mobility behavior. Further, we emphasize that we have not found any targeted attempt for deeply integrating travel rebound effects[11,12] i.e., demand changes resulting from increased use of information and communication technologies or autonomous vehicles, in ESMs.

Several reasons speak for the endogenous representation of some aspects of mobility consumer behavior in ESMs. Its representation leads to improved model independence, as it allows performing simulations without relying on the performance of an external model. Since many endogenous behavioral measures were tested and applied during the last years, it may still take some time until the modeling community will capture the most compelling features more frequently in models.

For representing technology choice and modal choice, a recent review suggests that heterogeneous consumer segments and a TTB, respectively, are best suited [22]. Further, consumer segments can allow representing an improved spatiotemporal resolution and heterogeneity, which is essential for reflecting mobility behavior in terms of electric charging accessibility (spatial distribution/density of charging stations), charging duration, and preferred charging times [7,28]. We echo such approaches due to their relatively low increased model complexity and low need for additional data, which are key advantages compared to most other options for implementing mobility behavior endogenously in ESMs. However, we acknowledge the limited availability of the required data in many countries. Further, we emphasize that these advantages are also valid for extending heterogeneous consumer segments with (income-specific) travel money budgets. Given the latest developments in this field, this can also improve the modal and vehicle choice decisions

[10] Examples of bounded rationality that influence vehicle purchase decision-making are brand preferences [170], social norms and status [171], confirmation bias [172], and emotional and affective decision making [173,174].

[11] Travel rebound effects refer to behavioral or systemic reactions that lead to a lesser reduction of mobility demand or its total energy consumption than what could be expected from technologies or measures that increase the efficiency [175]. Behavioral rebound effects reflect, for instance, an increased amount of mobility demand due to targeted information of information and communications technologies [31,176], and potentially increased mobility demand due to new mobility services like autonomous vehicles that could perform empty runs, make cars accessible to people that would otherwise not use them, and lead to relaxed travel time constraints [177,178].

[12] We emphasize that we are referring to travel rebound effects, which distinguish from economic rebound effects.

in technology-rich ESMs [46]. For instance, the travel money budget helps steer consumer decisions in models containing many vehicle technologies with differing investment and operational costs. Hurdle rates effectively integrate mobility behavior, as their implied costs can reduce the rapid domination of novel vehicle technologies in the market, and they are relatively simple to integrate into ESMs [20,39,43]. However, due to their linked challenges, we recommend that the implementation of hurdle rates should only be considered in models that aim for more advanced approaches of implementing mobility behavior parameters.

Driving patterns are currently mostly represented in a limited manner. An exemplary advanced approach could include individual intra-daily driving patterns representing the traffic conditions and driving speed of several aggregated trip types in different regions, which consequentially influences the fuel efficiency of the respective trips in the model. However, like ESM frameworks are not designed to represent individual consumers, they are also not designed to represent separate trips. Nonetheless, the inclusion of clustered trip types on a relatively high-level, that distinguishes aspects like trip distance, region, and time of the trip, would be advantageous for representing different driving patterns, their respective fuel efficiencies, and even the accessibility of certain modes for such trips. When integrating driving patterns for various trip types, they could be well combined with a suitable disaggregation of heterogeneous consumer segments with matching consumer clustering criteria, such as the living region and typical trip distances of consumers.

A set of reasons also speaks against the direct integration of consumer mobility behavior in ESMs. Most behavioral measures require a high amount of additional data, which often requires conducting large and complex surveys or making strong assumptions when translating qualitative data into quantitative model inputs. Moreover, a sheer number of linear programming ESMs traditionally focus on cost-minimization. This makes it challenging to integrate behavioral realism from a methodological perspective, as it is not trivial and often hardly feasible to translate behavioral parameters into cost-terms or specific preferences [119]. For instance, the calibration of quantitative hurdle rates provides challenges and uncertainties for selecting the 'right' values; a detailed discussion for determining plausible hurdle rate values is beyond the scope of this paper [120]. Consequently, endogenous model extensions can lead to larger and more complex models, resulting in high data requirements, data management overhead, long computational times, increased required computing power, and complicated interpretation of model outputs [4,121]. It should be considered that the applied ESM in [20,39] is a relatively simple prototype model that does not reflect different sectors of the energy system but only the light-duty vehicle sector, which raises the question if this approach can also be utilized effectively in more complex modeling frameworks. In essence, it can become challenging to effectively work with ESMs that reflect consumer mobility behavior endogenously, which is a limiting factor for endogenous model advancements.

Based on the insights of this review, we suggest the following good practices when enriching an ESM with the mobility behavior of consumers:

1. Focus on the most effective behavioral aspects for the purchase- and usage decisions for vehicles and transport modes. For instance, reflect spatial differences with a high temporal resolution by separating the population into heterogeneous consumer segments that can be attributed with the most suited aspects for representing their mobility behavior, as demonstrated with the MoCho-TIMES model for Denmark [46].
2. Consider potential behavioral rebound effects when representing novel mobility services, such as increased mobility demands from autonomous vehicles or more leisure trips when remote work becomes more popular.
3. Perform a careful trade-off between reflecting behavior and increased model complexity.
4. Remain endogenous flexibility within the ESM by implementing mobility behavior in ways that do not become predictive for the model outcomes, i.e., behavioral aspects should not exogenously fix the future decisions the model can make based on (past) consumer behavior. Otherwise, ESMs that cover multiple sectors could become rather predictive in the transport sector while other sectors remain a higher degree of endogenous flexibility.
5. Avoid too complex model structures that get very challenging to handle. In such cases, instead, consider model coupling to overcome the limitations of standalone models.

Overall, the critical point for the endogenous integration of mobility behavior in an ESM is the careful trade-off between increased model complexity, limited model flexibility, and an improved mobility behavior representation. Therefore, this review will go one step further by providing an in-depth analysis of model coupling approaches that can overcome this limitation and, therefore, provide additional benefits in contrast to the endogenous implementation of mobility behavior.

3.2. Model coupling

This section discusses the previously outlined coupling approaches for representing mobility behavior. A discussion of the general advantages and challenges of model coupling approaches is provided in Appendix D.

Model coupling approaches have been performed with different model types to represent specific characteristics of mobility behavior. Each approach considers consumer behavior through at least one of the involved models. The aims of the reviewed model couplings can greatly distinguish and influence which type of models should be selected for the coupling (see Table 3). For practical reasons, it might frequently happen that several models are available for coupling, and based on that, a suitable research question is determined. However, to cover strong and stringent research questions, modelers should first determine their qualitative goal and then select feasible models that allow combining different perspectives to provide insights for that goal. The wide variety of possible model combinations shows that model coupling can represent many facets.

The ultimate goal is typically to improve the future pathway analyses for mobility demands, energy consumption, and greenhouse gas emissions. To achieve this, the reviewed model couplings focus on different facets. To infer the mechanisms of model coupling from the goals identified in Table 3, we provide practical modeling insights from a goal-oriented perspective:

1. **Integrate behavioral realism of the transport sector into the interplay of the entire energy system:** The entire energy system greatly influences the transport sector. Especially the energy supply and the infrastructure deployment for electricity supply and charging, as well as the residential situation of consumers, influence their mobility choices and the accessible mobility services and infrastructure, steering the consumer mobility behavior. In turn, the mobility behavior affects fuel prices, the need for such supply infrastructure, and mobility service and influences if other sectors of the energy system require stronger or less strong decarbonization to achieve climate targets. To reflect the critical impacts of other energy sectors on the mobility behavior and vice versa for potential future mobility pathways, we emphasize the importance of a systemic energy perspective for model coupling approaches that include mobility behavior. As shown in Table 2, most of the reviewed model coupling approaches include a systemic energy perspective. Often, such a model was the starting point for the model coupling. Thus, the following goals build upon the existence of the systemic perspective,

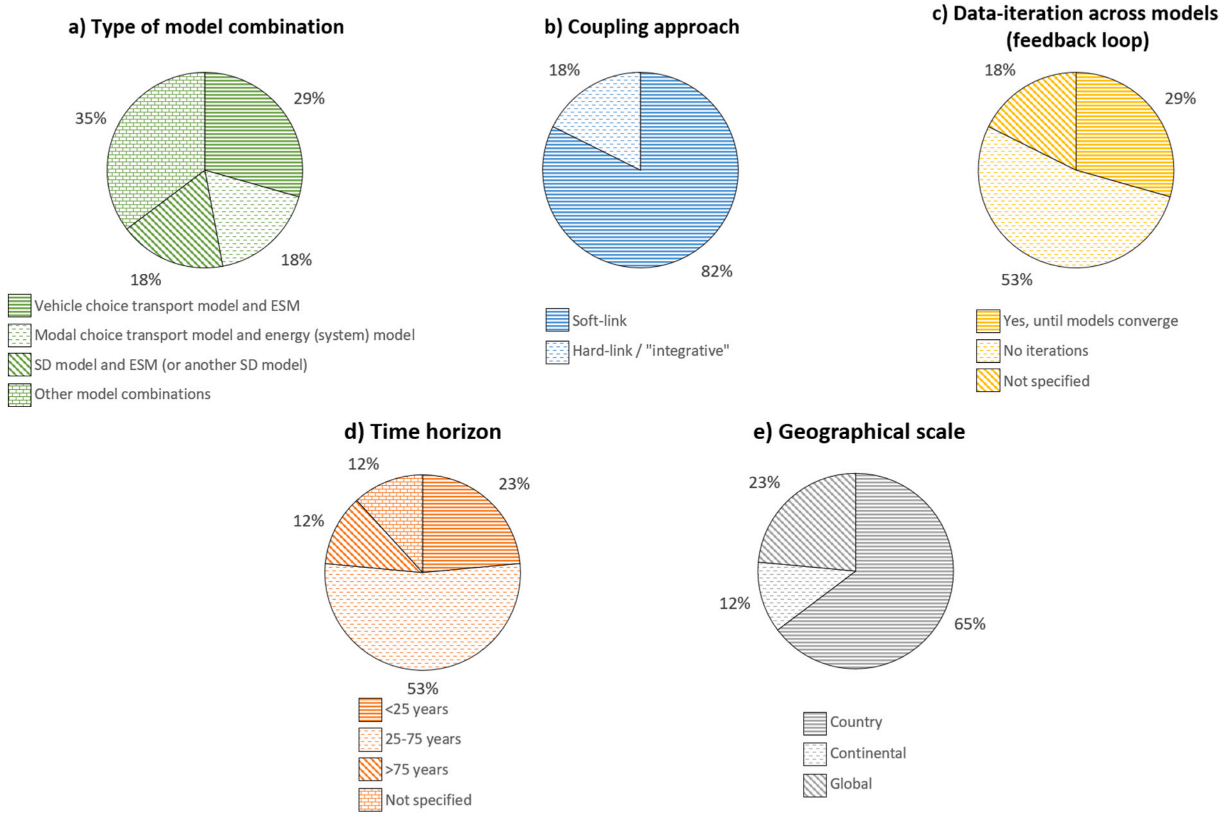

Fig. 2. Overview of literature with relevant model linkages for mobility behavior. Each graph shows the number of model couplings (N = 17) for the a) included type of models, b) their coupling approach, c) data-iteration across the models (feedback loop), d) time horizon, and e) geographical scale.

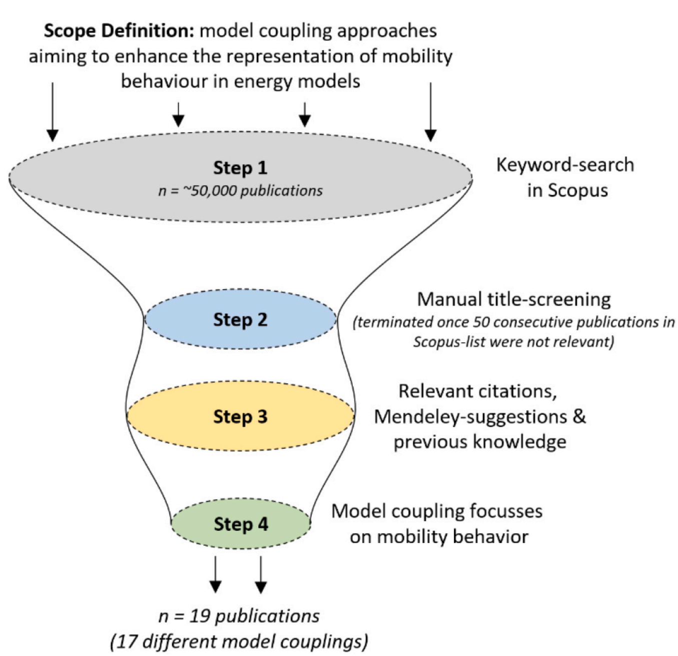

Fig. 3. Collection and selection of relevant literature. The review methodology is exemplarily visualized for the model coupling approaches.

and the coupling goals intend to enrich this from a behavioral perspective.

2. **Improved vehicle purchase choice behavioral realism:** This objective can be tackled by including a behaviorally-detailed vehicle choice transport model in the coupling framework. It enables to provide vehicle choice decisions to another model and, in turn, to use the results of the external model (e.g., fuel prices) to influence the vehicle choice of consumers. The linkage mainly requires data harmonization by suitably aggregating/disaggregating the available technologies and consumers in each model.
3. **Improved modal choice behavioral realism:** This goal requires implementing a mode choice transportation model that incorporates consumer realism into the coupling framework. By providing more realistic modal shares to another (energy) model, the latter can typically generate systemic insights for improved technology choices, fuel consumptions, fuel prices, and more. In an iterative approach, such aspects could again serve as inputs for updating the mode choice.
4. **Mobility service and charging (infrastructure) demand assessment:** To assess such demands, the impacts of consumer lifestyles and the feedback between energy supply and EV charging are determined. For the former, stringent lifestyle scenarios are constructed. Model coupling enables to evaluate the interdependencies of such lifestyles with mobility choices and other sectors of the energy system. For the latter, the detailed charging behavior of consumers and their mobility demand can reflect their electricity demand. Model coupling allows assessing the impacts of such a detailed model in a greater perspective for the transport sector or the entire energy system.
5. **Impact of behaviors, policies, and costs on the market penetration of novel vehicle technologies:** To evaluate the dynamic non-linear impacts from a broad palette of aspects and different market players (users, authorities, infrastructure providers, and manufacturers) on the market penetration of novel vehicle technologies, an SD simulation model of the transport sector was used in the reviewed literature. Similar to the previous category, the model

coupling with other models enables to assess the insights of such a detailed model in a broader perspective.

It should be noted that this list does not contain all possible goals but focuses on the most common ones in the reviewed literature. New goals will emerge, and other aspects of mobility behavior will be examined more frequently with more model coupling approaches investigating mobility behavior in the future.

A limiting factor for this review was the lack of discussion in the reviewed literature about limitations in the methodological coupling framework (see Table 3). While the limitations of the individual models within a coupling framework are discussed frequently, an overarching perspective regarding aspects like challenges for suitable data exchange or consistency issues across the different model frameworks is missing.

Fig. 2 provides an overview of the model coupling approaches in the literature that consider mobility behavior. Fig. 2a shows a spread over the different kinds of model coupling groups. Fig. 2b shows that most coupling approaches apply a soft-link. In contrast, a hard-coupling or 'integrative' approach was performed three times. This choice of modelers reflects that the hurdle to apply soft-linking is lower, which is likely due to the lower requirement for automated data processing between the models. According to Fig. 2c, most linked models do not iterate the data; only five iterative simulations are performed until convergence is reached. Missing data iterations are frequently mentioned as a potential avenue for future work in the analyzed publications. Fig. 2d shows that mostly long-term timeframes of more than 25 years into the future are simulated. Such long timeframes typically come with challenges when using historical mobility preferences to project future developments. This raises the open question of how reasonable it is to estimate mobility behavior over such long time periods [122]; something that requires further investigations from the research community. Fig. 2e reflects that mostly a single country is represented.[13] This seems reasonable as it is crucial to determine a good spatial coverage and respective spatial resolution to represent different mobility preferences based on the geographical surroundings[14] for simulating mobility behavior.

When models are coupled for enhancing mobility behavior, it should be carefully examined which parameters can be exchanged among models and how such data need to be pre-processed to ensure consistency and correct data formats. Thus, it should be evaluated which model outputs provide beneficial information as inputs for the other model and help answer the research question. Mostly, a model with a detailed representation of mobility behavior can be combined with a model with no or limited mobility behavior. Thus, as each model typically computes a simulation around its core purpose and then provides feasible data that suits the core purpose of the other model, the exchanged data are typically parameters that are not directly representing mobility behavior (see Appendix C). Nonetheless, the couplings enrich the insights and impacts of mobility behavior, as the exchanged data values are triggered from applying, for instance, behavioral parameters within one of the models. Mainly, one model focuses on targeting mobility behavior, while the other model is not or to a limited extent focused on mobility behavior (often ESMs, which in some cases include aspects of mobility behavior). In some cases, the applied models exchange data by being integrated into another model instead of being individual models [34,37]. In such cases, the models are hard-linked and can be understood as separate modules of one larger model framework.

Translating qualitative consumer behavior into quantitative model inputs for the endogenous representation of mobility behavior in a standalone model often comes with uncertain assumptions. This can quickly lead to over- or underestimating the impact of mobility behavior on the model output. This leads to a precondition for pursuing model coupling with an ESM that contains such parameters: the quantitative assumptions that aim to represent qualitative behavior need a thorough assessment and sensitivity analyses because they will propagate errors to the connected models. The connected models would, in turn, exacerbate the problem in subsequent looping and jeopardize convergence. Avoiding such negative induced impacts is crucial. Therefore, each involved model should first provide a robust individual performance within its scope on its core task before focusing on the coupling.[15]

3.3. What is the value of model coupling compared to endogenously integrating mobility behavior in ESMs?

In the previous sections, we have outlined the pros and cons of both concepts for considering mobility behavior in models. This section goes one step further by evaluating the value of model coupling compared to endogenously integrating mobility behavior measures in ESMs.

Despite advancements during the last decade to represent behavioral aspects in standalone models, it is not always possible to integrate or improvise behavior in single modeling frameworks due to methodological limitations [123]. Based on this review, the integration of mobility behavior in cost-minimizing ESMs comes with the challenge of a limited scope for representing non-techno-economic parameters. Moreover, this requires a high amount of additional data, leading to increased model complexity and computational resources. Furthermore, relatively fast changes in the energy supply sector and the emergence of new technologies and mobility services confront ESMs with challenges due to increasing complexity while requiring more flexibility and cross-sectoral interactions in the energy system [124].

Applying model coupling can allow one to tackle and overcome such challenges. This is due to the ability of linked models to combine insights from different perspectives on one topic while letting each model keep its focus on its core purpose. With this, each model can remain a well-defined structure around its core purpose, manageable complexity, faster computational times, and produce outputs that can be easier interpreted. In combination, complementary models can provide more robust and profound insights into the impacts of mobility behavior. When applied iteratively, they allow reflecting behavioral dynamics and behavioral rebound effects through induced feedback loops. Especially for considering mobility behavior, it is advisable that one model has its core around the consumer mobility behavior and requires and/or delivers data that can serve as connection points for a complementary model, which provides, for example, systemic insights. Moreover, when a new parameter needs to be considered in the combined framework, it can be integrated into the model that is best suited for representing this parameter, instead of finding ways for representing them in a standalone ESM that often has a cost-minimizing framework. As the focus of the model can remain in model coupling on its key area, the model is more flexible to be applied in several model coupling approaches in parallel. Thus, each aim and research question can be tackled with the most suitable combination of other models. It is essential to ensure continuous improvement of knowledge gained through the coupling when the separate models can still be applied individually. Therefore, modelers

[13] This includes the publication of Mulholland et al. [85] where two countries (Denmark and Ireland) have been simulated. For simplicity, we merged this publication in Fig. 2e with the model couplings that represent a single country.

[14] For instance, the geographical surrounding may lead to significant impacts for the accessibility of *E*-charging infrastructure. Alternatively, a person living in the mountains may have an increased need for a higher motorized vehicle in comparison to a person living in an urban area.

[15] For instance, when combining a behavior-oriented transport model with an ESM, it first should be ensured that the behavior-oriented model shows a reasonable performance when representing impacts on and from mobility behavior, while the ESM should have a good representation of reflecting cross-sectoral effects in the energy system relevant for the transport sector (e.g., simulating if enough low-carbon electricity can be produced at competitive prices to fuel respective vehicles, and considering cross-modal effects within the transport sector).

should develop techniques that maintain the main dynamics of a previous model coupling in the separate models for future standalone applications or iterations in other coupling frameworks. Otherwise, future model coupling activities may neglect systemic interdependencies tackled in a previous model coupling activity. As this strain of research is not covered in the reviewed literature, we stress its importance for achieving continuous model enhancements.

The validation of model input data and results is an ongoing challenge for the modeling community and affects both reviewed concepts for representing mobility behavior, standalone models and linked models [7,125]. In the reviewed model coupling publications, the validation of the combined approach is rarely mentioned and vague. Some cases refer to the validation of the individual models. While the validation of the individual models should be a prerequisite for robust model coupling, we stress the importance of establishing a set of aligned validated input data shared by all models within a model coupling and validating the entire model coupling framework as a whole. In general, the selected modeling concept has low relevance when the assumptions for future behavior are poor [126]. However, the validation of behavioral data is challenging because the future change of mobility behavior contains a high level of individual variability, and it can be influenced by many aspects that are prone to deep uncertainties in their future development, such as broad societal shifts in values and norms, disruptive events, and novel technologies [26,125]. Common approaches for validating models include sensitivity und uncertainty analyses [26,103,125], expert judgment [44,125], stylized behavioral patterns [26,125], ex-post modeling [26], calibrating the model inputs to fit historically observed data with the model outputs [103], and field studies [127]. Those approaches can also be applied to validate mobility behavior. Especially for validating consumer behavior, it could be useful to combine quantitative and qualitative methods to take advantage of their individual strengths for validating overarching correlations and expressing complex decisions, respectively [2].

In essence, modelers should seek to integrate mobility behavior in standalone ESMs endogenously when the behavior-related data fit into the modeling framework and comes with a relatively low increased model complexity. This is typically the case for stylized behavioral facts (e.g., TTBs and TMBs), usage patterns, the accessibility of certain technologies or (EV charging) infrastructures for consumers, and behavioral aspects that can be quantified in cost-terms. In addition, standalone ESMs can effectively distinguish relatively large groups of the population that show different mobility preferences or distinguish broadly defined trip distances that different transport modes can fulfill. This modeling concept is beneficial when consumer behavior that can be generalized across the population and is not highly individual is integrated. It provides the advantages of less complex and more independent model enhancements without the methodological extra-work necessary for setting up and performing model coupling. Further, modelers should aim to maintain the main dynamics of a previously applied model coupling to keep representing the systemic interdependencies in an individual model.

Suppose modelers seek to investigate more complex research questions that investigate deeper and more nuanced behavioral preferences of different consumers and market players. In that case, model coupling can offer advantages over integrating mobility behavior into standalone ESMs in several ways. When different modeling perspectives/frameworks on the transport- and energy system should be assessed, combining different modeling frameworks in a joint approach provides more flexibility in representing behavioral (and other) aspects. This is especially substantial in the transport sector, where many players (e.g., consumers, infrastructure providers, car manufacturers, and policymakers) interact with different goals, behavioral preferences, and objectives that often clearly deviate from a cost-optimal solution that ESMs typically calculate. With model coupling, it is simpler to consider behavioral choice preferences that are challenging to be represented as cost terms and provide insights beyond a cost-optimal solution. This allows one to easier apply non-cost aspects as relevant criteria for the simulation, and a broader set of dimensions can influence consumer decisions. Further, model coupling shows advantages for representing nuanced preferences of many individual agents in a systemic energy context. This allows deeper investigations of the interplay between preferences of different consumers and other players of the transport system, as well as of the effects that they have on each other and, in turn, on the energy system as a whole.

3.4. Recommendations for future research

Based on the previous discussion insights, we provide future research suggestions to achieve improved mobility behavior representations in energy models.

For standalone ESMs, we suggest extending models with measures that improve the vehicle- and modal choice of consumers without significantly increasing the model complexity and data requirements of the model. Suitable measures for this are implementing heterogeneous consumer segments like Ramea et al. [39], but each segment combined with their respective TTBs and income-specific travel money budgets [45]. Implementing more complex mobility behavior measures to an ESM is possible via, for instance, disutility costs or hurdle rates, but this leads to previously outlined challenges. At the same time, it should be kept in mind that the computational times should stay in acceptable ranges; methods for this have been analyzed by Scholz et al. [128]. In addition, we suggest strengthening the representation of new mobility trends such as Mobility as a Service or autonomous vehicles, including their potential rebound effects, which could strongly impact future mobility preferences. While such emerging aspects deem important and perceive an increased interest within the ESM community [28], we did not find appropriate approaches for modeling them. Overall, endogenously integrating mobility behavior measures in ESMs enables them to provide more substantial and more realistic insights, but it requires a careful trade-off between potential benefits and increased model complexity.

For model coupling approaches, the ideal types of combined models depend greatly on the research questions to be investigated. In general, we recommend combining systemic energy models with behavior-centered models, as this enables to represent mobility behavior with greater detail within a systemic perspective. This is of paramount importance, as the changing energy system[16] provides implications for the usage of transport technologies and opportunities for other technologies to penetrate the energy system. Furthermore, feedback loops should iteratively exchange the data until the results converge to reflect the systemic changes induced by behavioral mobility dynamics and vice versa.

Importantly, both concepts for representing mobility behavior reviewed in this work should not be considered exclusive. Instead, the concepts can complement each other: an ESM that considers selected aspects of mobility behavior can improve the possibilities for exchanging data with a linked behavior-centered model. Thus, better data integrity between the coupled models can be achieved. Further, the data can be exchanged with finer granularity. For example, when an ESM represents some aspects of mobility behavior in a simple form and iterates its outputs with a model that contains sophisticated mobility behavior representation, this could help tune the reduced representation in the ESM to let it better emulate the external model in a specified parameter space. Therefore, combining both methodological concepts reviewed in this work can allow overcoming their limitations while amalgamating their strengths.

[16] For instance, increasing hydrogen supply, market penetration of EVs, and opportunities for utilizing the electricity storage capacity within the transport sector to provide an increased flexibility for integrating variable renewable energy sources into the energy system.

To validate an entire model coupling, we recommend applying cross-model comparison to determine if the results are within the range of a certain expectation horizon. When data-iteration is applied, this comparison with the expectation horizon should be made after each iteration to express in which range the results evolve. An application of such a comparison as well as an extensive discussion about model validation are outside the scope of this paper. Nonetheless, the development of solid validation approaches and clear communication of hardly verifiable assumptions for future consumer behavior are crucial to provide policymakers with better tools and increase the credibility of standalone models and model couplings.

We call for more awareness among scholars to provide detailed insights on the methodologies and bottlenecks experienced when applying model coupling and critically evaluate the applied coupling approaches. We emphasize three observations that repeatedly occurred during the literature review. First, when models are iterated, it often remains unclear how the results developed over the single iterations and how many iterations were required until convergence was achieved. It is rarely reported that iterative coupling did not lead to convergence, which raises the question of whether convergence was mainly achieved with the first attempt or unsuccessful attempts were not reported. However, knowledge about failed convergences could provide helpful insights for other modelers to learn about potential sources of errors and how to overcome them. We acknowledge that such information might be subject to discussions in conferences rather than being published in articles. Still, given that model coupling for mobility behavior often brings scientists from different disciplines together, we believe it is in the interest of future advancements in this field to emphasize such information in written publications. Second, the reported information sometimes show a lack of detail about how data are exchanged between the models. While it is mostly evident in which sequence models have been applied, more information about the required data-processing between the models and if validity checks of the interim data are performed would be helpful for peers. Thirdly, many publications about model coupling focus their discussions on the results and often neglect a critical review of the applied coupling methodology. For instance, it often remains unclear if and how non-linear aspects of mobility behavior were integrated into linear model frameworks and which influences this had for the solvability of the models. In summary, more detailed information on such issues could substantially help the research community apply model coupling more effectively.

Future work on model coupling could achieve deeper insights into mobility behavior by enhancing the applied methodologies. Typically, models are being computed in sequential order, meaning that first the one model is simulated over its full time horizon and provides data to the other model that subsequently simulates its full time horizon, and vice versa. Such approaches could be enhanced by an interleaved co-execution of the models. In such a case, the models exchange data at every timestep of the computation, as proposed by a novel research project [129]. With this approach, each model considers the implications of the feedback from the other model when computing the next timestep. This could deliver deeper and more dynamic insights into the impacts of mobility behavior. However, the possibilities for such an approach must be weighed for each model individually, as this may not always be possible in models that optimize over their entire time horizon. In addition, a broad palette of instances can influence real-world mobility behavior, ranging from individual aspects on the micro-level to societal shifts of norms and values on the macro-level. Thus, future work could couple new combinations of different model types to reflect different perspectives of the nuanced real-world mobility behavior. For example, rebound effects, bounded rationality, or the impact of governance on shifting mobility behavior and social acceptance are crucial aspects for the future transition of the transport system but have not yet sufficiently been represented in model coupling approaches. Further, exploring the possibilities of modern computing advancements for applying self-learning algorithms could be an interesting avenue for future enhancements. Such algorithms could, for instance, test the robustness of a model coupling framework by exchanging different sets of parameters between the models, identify the most/least sensitive parameters within a model or model coupling, or improve how agents in an ABM react in certain situations. Finally, we recommend strengthening the interplay between the different actors in the transport system, i.e., consumers, governments, car manufacturers, and transport service providers, in models for considering a broader sense of mobility behavior. Therefore, a more substantial representation of the mutual impact that the different transport sector actors have on each other would help to analyze their interaction in more depth in the future.

4. Conclusion

This work provides a systematic review of methodologies that aim to improve mobility behavior representation in future-oriented computational models. Two commonly used concepts are analyzed, viz. endogenously implementing mobility behavior measures in energy models and representing mobility behavior via model coupling approaches. This paper has answered three research questions (see Section 1) on representing consumer mobility behavior with those two concepts.

The existing methods for both concepts are reviewed and presented in detail. We identified the challenges, limitations, and opportunities for representing mobility behavior by each concept and provided suggestions on good practices for applying the concepts. Standalone ESMs made substantial improvements for endogenously representing mobility behavior in the last decade. They focus on implementing mobility behavior in terms of stylized facts (e.g., TTB, TMB, travel time investments), inputs from external models/reports, driving times, the possible substitution of transport modes based on trip distances, and translating behavioral preferences, discomforts, and investment hesitancies into cost-terms. Such enhancements are becoming more commonly combined with heterogeneous consumer segments. Model coupling has been increasingly applied within recent years to represent mobility behavior. Different types of models can be combined depending on the research questions to be answered. Thus, the best and most practical choice for representing mobility behavior depends on the scope and complexity of the available model(s), data availability, computational resources, the modeler's know-how and expertise, and the examined research question.

This review discussed which concept is more feasible in certain scenarios to help the research community select the most suitable methodology for a defined research goal. We conclude that standalone ESMs are beneficial when light stylized behavioral parameters that can be generalized across consumer groups and cultures can be incorporated into the typically cost-optimizing framework of such models. However, this concept faces methodological limitations, such as data requirements, modeling framework, and limited model flexibility, which well-designed model couplings can overcome. The latter is superior for integrating different perspectives in more complex analyses. This is critical when individual mobility behavior should be combined with a systemic view of the energy system. Also, model coupling proves particularly beneficial in representing preferences of individual consumers and different actors of the transport sector in a systemic energy perspective, compared to endogenous improvements in a standalone ESM. However, a good coupling approach requires that each model provides consistent results within its scope. Thus, it is essential to co-develop the individual models and their combined coupling approach. Consequentially, both reviewed concepts for representing mobility behavior should be viewed as complementary to each other to merge their individual strengths. For instance, coupling an ESM with endogenized aspects of mobility behavior with a behavior-centered (transport) model can improve data integrity.

There are several options for further investigating the research on the two reviewed concepts. This work provides recommendations for future work to build upon the broadly shared methods across the existing literature. Besides exploring the complementary nature of both investigated concepts, future work could compute the coupled models in a timestep-wise interleaved sequence to gain deeper insights into the connection between the market diffusion of new technologies and behavioral transport dynamics. In summary, the future work recommendations seek to close existing research gaps and identify novel research avenues that could levitate the representation of mobility behavior to a higher level.

CRediT authorship contribution statement

Sandro Luh: Conceptualization, Methodology, Formal analysis, Investigation, Writing - Original Draft, Writing - Revision, Visualization, Project administration. **Kannan Ramachandran:** Conceptualization, Writing – Review & Editing, Supervision, Funding acquisition. **Thomas J. Schmidt:** Writing – Review & Editing, Supervision. **Tom Kober:** Writing – Review & Editing, Supervision, Funding acquisition.

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.

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Appendix A. Review methodology

The literature search for this review paper followed a structured and systematic approach. The following description should allow others to replicate this search.

In a first step, the literature database Elsevier Scopus, one of the largest literature databases on the internet, has been used with a pre-defined combination of keywords within multiple layers to find relevant papers [130]. The keywords within each layer have been combined with the logical operator OR. The single layers have been combined with the logical operator AND. Two sets of searches were performed, viz. 1) endogenous implementation of mobility behavior in standalone ESMs (see Section 2.1) and 2) model coupling approaches aimed at enhancing the representation of mobility behavior in energy models (see Section 2.2). Fig. 3 visualizes the process for collecting and selecting relevant literature exemplary for set 2. The first set has the following search layers:

- In the first layer, we are primarily interested in passenger transportation and therefore used the keywords mobility, transport*, car, bus, train, and plane.
- The second layer was targeted at behavioral aspects. We used the following keywords: behavio*, social, Rebound Effect*, and Indirect Rebound*.
- The third layer contained keywords related to relevant model types: Energy Model*, Energy System* Model*, IAM, Integrated Assessment Model*, Transport Model*, mobility model*.

The first set of the search generated a total of ~5000 publications, ranging from journal articles to reports to doctoral theses. For the second set, i.e., model coupling approaches,

- the first layer aimed to find techno-economic models with the keywords Model*, Tech*Economic*, TIMES, GENeSYS, OSeMOSYS, MARKAL, DLR, and “Energy system*”.
- The second layer contained keywords related to behavioral-economic models: Model*, Behavior*Econom*, Behavior*Science*, Soci*Science*, long-term, and Behavio*r*.
- The third layer intended to filter for articles that include a coupling or linking aspect between such models and used the keywords Coupl*, Copl*, Link*, iteration, soft-link*, hard-link*, hybrid*.
- The fourth layer referred to additional attributes such as the focus on transportation and long-term analyses and included the following keywords: long*term*, scenario*, long*time*, transport*, mobility*.

The search of the second set was further focused by selecting relevant subject areas, which resulted in a total of ~50,000 publications.

In a second step, the results were sorted by their relevance using Scopus. Then, titles of the papers were manually screened to shortlist publications that seemed relevant to the scope of this paper. Due to the high number of search results, the manual screening was terminated once 50 consecutive publications in the Scopus list were not relevant for this review topic.

In step three, some additional relevant publications were found through references in the screened articles from step two using the reference management tool Mendeley and through relevant articles that came to the authors’ knowledge before and during the examination of this review.

For set one, i.e., endogenous implementation of consumer behavior in standalone ESMs, Venturini et al. [22] provide a comprehensive review with an overview of this topic. Section 3.1 summarizes their key findings and complements them with additional literature and the most recent developments to guide the reader. For set two, i.e., model coupling approaches that enhance mobility behavior in energy models, we shortlisted 57 publications through steps 1 to 3, which have been reviewed more extensively. Some publications describe integrated model frameworks that consist of different ‘models’ but are out of scope because the consisting models have been built together from scratch to develop the framework, e.g. [131], instead of combining different existing models via coupling. We acknowledge the existence of even more model coupling publications, but they are outside the scope of this work. For the shortlisted publications, we systematically reviewed each of such publications in terms of geographical coverage, time horizon, coupling type (soft- vs. hard-linking), scope, objective, the purpose of their application (for instance, analyzing scenarios or testing a hypothesis or methodology), research questions, and coupling approach. Regarding the coupling methodology, the emphasis was on the model application sequence, and the data and parameters exchanged across the models. The limitations and outlook have been critically reviewed.

Finally (step 4), for the model coupling approaches, it was determined whether the coupling emphasizes the transportation sector and its consideration of behavioral aspects. Thus, some were sorted out of the shortlisted research publications as they present generic model couplings without explicitly emphasizing the transport sector [69,119,132–160]. Five of the remaining transport model coupling publications did not consider dedicated mobility behavior aspects [161–165]. Such publications, where not both aspects hold, have not been further considered for this review's in-depth model coupling analysis. The remaining publications cover model coupling approaches that emphasize mobility behavior and are covered in Section 2.2. A comprehensive list of such research publications is provided in Table 2.

Appendix B. Detailed description of each model coupling approach relevant for mobility behavior

B.1. Vehicle choice transport model and ESM

The most common group to consider mobility behavior through model coupling is combining a purchase-oriented vehicle choice transport model with an ESM. Typically, this enables to represent consumer behavior when making vehicle purchase decisions.

Daly et al. [73] were, to our best knowledge, the first in performing such a coupling approach between an ESM and vehicle choice/stock model with relevance to mobility behavior. They soft-linked the Irish TIMES energy system optimization framework [88] with the Car Stock Model [89]. The latter provides vehicle selection and mobility demands (in personal kilometers) to the former. By doing so, each model utilizes its strengths, i.e., the Irish TIMES model interacts with other sectors on the energy system, and the Car Stock model can make use of its highly disaggregated vehicle technologies that consumers can choose from. Building upon such developments, Mulholland et al. [74,75] apply a model-coupling that combines the same two models, Irish TIMES [88] and CarSTOCK [89] (the naming convention of the latter model changed compared to the previous publication [73], but it is the same model and has evolved over time), with the CIMS market share algorithm [90]. The exchanged data between the soft-linked Irish TIMES model and the CarSTOCK model became more advanced: after the Irish TIMES model generates a technology pathway to reach a pre-defined long-term CO_2 target, the respective energy efficiency improvements and fuel switching effects in the private car fleet are extracted from Irish TIMES to create policy roadmaps in the CarSTOCK simulation model. They further enriched this framework by linking the Irish TIMES and the CarSTOCK model separately to a market share algorithm model to represent heterogeneity and varying consumer preferences for new technologies. This allows capturing socio-economic drivers related to costs and intangible costs, such as range anxiety and the hesitation of consumers towards buying novel vehicle technologies.

Tattini et al. [72] went one step further in their soft-coupling of the Danish ESM TIMES-DKMS [59] with the techno-socio-economic Danish Car Stock Model (DCSM) [72] by modeling not only car choice but also a modal choice. Both models take specific measures for representing behavioral realism into account: TIMES-DKMS accounts endogenously for modal shift. It provides cost-optimal vehicle technology investment for the model coupling. DCSM consists of a socio-economic consumer choice simulation model [72] and the techno-economic CarSTOCK simulation model [85]. It provides detailed consumer preferences regarding vehicle choice, leading to a private car fleet composition according to such preferences. If it comes to an infeasible solution, TIMES-DKMS is enriched with capacity constraints representing car share projections from DCSM. This procedure is iterated until both models converge in private car fleet compositions. They achieve giving more realistic insights into the needs to achieve climate goals in the transport sector by considering several transport modes. However, one limitation is that modal shift is determined based on socio-economic constraints and does not consider consumer heterogeneity.

An alternative approach by Anable et al. [71], which also considers different transport modes, makes use of different lifestyle storylines and soft-links the MARKAL Elastic Demand (MED) ESM [92] with the sectoral UK Transport Carbon Model (UKTCM) [37,91]. They analyze the combined effects of behavioral change and technological change to reach emission reduction targets. For this, the UKTCM determines in a first step its inputs for transport demands from different structured lifestyle storylines, which reflect societal preferences due to shifts in non-price determinants of behavior and non-consumptive elements of behavior. In a second step, also policy shifts are considered that empower the consumers to execute their choices. With such different lifestyle storylines, UKTCM generates outputs for vehicle choice, vehicle use, vehicle ownership, and fuel consumption. These outputs from the UKTCM are aggregated over car sizes (MED has only one car size) and translated into inputs for the MED system model. Such inputs include sectoral technology mixes and -deployment (but Anable et al., 2012 focusses on the transport inputs only), vehicle fuel efficiency, distances traveled by transport mode, and resulting fuel demand and CO_2 emissions. MED simulates the final traffic levels, technology mixes, and modal shares by assuming a lower discount rate for lower-carbon and energy-efficient vehicles for representing shifts in consumer preferences. However, the outputs from MED were not used to apply a feedback loop between the models.

Wulff et al. [76] link three models in sequential order to find impacts from user behavior for electric vehicle charging on the energy system. By substituting two different EV charging models [93,94] with each other in their combined approach with a vehicle fleet model [95] and an ESM [96], they compare the influences of a more or less flexible electric charging infrastructure and charging behavior.

B.2. Modal choice transport model and energy (system) model

Combining a dedicated modal choice model with an energy (system) model allows an improved representation of modal shift, which is vital to achieving climate targets.

Schäfer and Jacoby [79] have performed a model coupling approach within this group. They combined on a global scale the technological MARKet ALlocation (MARKAL) model [97], the economic MIT Emissions and Policy Analysis (EPPA) model [98], and two transport-specific modal split models for passenger and freight transport [45], respectively. MARKAL, a precursor of the TIMES family of models, is a bottom-up techno-economic model that finds cost-optimized technology pathways for satisfying a given transportation demand. EPPA is a CGE model representing transportation as a nest of constant substitution elasticity within its household and industry sectors. While the EPPA model usually determines the transport mode choice internally, the mode choice is in this model coupling approach determined by the dedicated modal split model that takes consumer behavior into account through a daily TTB combined with travel speeds of the different modes of transportation. The applied approach distinguishes between the calibration and simulation stages for coupling the three models. In the calibration stage, the three models exchange data iteratively until convergence concerning total energy use in the transport sector is reached. For this, MARKAL provides substitution elasticities and autonomous energy efficiency variables to EPPA. EPPA provides the absolute transport demand to the modal split models, which in turn provide modal shares to MARKAL and structural changes to EPPA. In the simulation stage, EPPA provides MARKAL directly with fuel prices, taxes, and transport demands without further iterations. Subsequently, MARKAL determines the overall results of the coupling approach, i.e., the vehicle technology penetration on the market. This study was a forerunner in coupling computer models that use coupling to integrate some mobility behavior.

Some years later, Girod et al. [34] integrated the global passenger transport model TRAVEL into the TIMER energy model, which is part of the IMAGE IAM [99] and feeds TRAVEL with data. TRAVEL is a global transport model based on MNL equations that connect seven transport modes and 22 different car types, respectively. Key drivers for the mode choice in this model are the two behavioral parameters representing empirical observations regarding the constant travel income budget and a daily TTB. In contrast to the constant TTB seen with Schäfer and Jacoby [79], Girod et al. [34] assume annually an increase of 0.25 min in the TTB per day.

A coupling approach that takes many behavioral aspects other than travel income and TTB into account has recently been developed by Tattini et al. [78], who developed a soft-link between the Danish ESM TIMES-DK [100] and the Agent Based Modal Shift model of Denmark (ABMoS-DK) [101]. TIMES-DK provides a holistic view of the Danish energy system. ABMoS-DK simulates transport mode choices by taking travel behavior insights from a travel survey of the Danish population into account. This approach aims to find the policy impacts on modal shares and the meaning of such from the perspective of the whole energy system. The coupling is initiated by ABMoS-DK, which considers the impacts of policy measures to provide modal shares. Such modal shares are fed into TIMES-DK, which provides, in turn, fuel prices. The fuel prices of TIMES-DK are implemented back into ABMoS-DK to establish an iteration between both models. Once the results converge, TIMES-DK provides the final results regarding total system costs, infrastructure investments, fuel consumption, and CO_2 emissions.

B.3. SD model and ESM (or another SD model)

Another group to consider mobility behavior with model coupling is combining a SD model with an ESM or another SD model. This allows broadening the scope from consumer-focused analyses towards taking the different transport market players into account. The Powertrain Technology Transition Market Agent Model (PTT-MAM) [102,103] is used in each of the three approaches. PTT-MAM is an SD behavior-based ABM representing four stakeholders within the EU transport market, i.e., users, authorities, infrastructure providers, and manufacturers.

Thiel et al. [80] outline a palette of five models, i.e., PTT-MAM [102,103], the fleet impact model DIONE [104], the Electric-vehicle charging model EV-charge [105], the European energy system optimization model JRC-EU-TIMES [106], and the GIS-based charging infrastructure allocation tool GIS EV Infra [107]. While the study outlines that “the models are soft-linked” [80], it does not explain the respective coupling methodology or results from the model coupling. However, the model most relevant for mobility behavior, PTT-MAM, has been applied in coupling approaches during follow-up works: Blanco et al. [81] soft-links the PTT-MAM [102,103] with the JRC-EU-TIMES [106] model, a multi-regional EU energy systems optimization model. This linkage aims to provide improved policy recommendations by combining the complementary strengths of each model. First, both models are harmonized for the covered user categories, the number of energy carriers, the base year calibration, and assumptions for future population development and technology availability. Then, the JRC-EU-TIMES model is simulated and provides PTT-MAM with fuel prices, fuel investments, overall mobility demands, emission targets, and energy consumption. Two different approaches were tested to feedback data from PTT-MAM to JRC-EU-TIMES: the first approach did overwrite the powertrain choices from JRC-EU-TIMES in PTT-MAM in order to feedback the behaviorally more realistic powertrain market shares (by country or at EU-level) from PTT-MAM to JRC-EU-TIMES. Two iterations were sufficient to achieve convergence between both models. The second approach leaves the powertrain choices within JRC-EU-TIMES and feeds the CAPital- and OPerational EXpenditures (CAPEX and OPEX) from PTT-MAM back to JRC-EU-TIMES. The study found that the first approach was more beneficial as it allows to make use of the behavioral aspects within PTT-MAM. Gómez Vilchez and Thiel [82] soft-linked the PTT-MAM [102,103] with the Transport, Energy, Economics, Environment (TE3) model [108] with the aim to shed light on the possible deployment of EVs on a broad international scale. TE3 is a SD model that distinguishes across four consumer segments (innovators, utility maximisers, low-cost buyers and habit-oriented purchasers) for finding the impacts of cars on energy demand and greenhouse gas emissions. The models simulate the uptake of EVs in the EU, and in China, India, Japan and the USA, respectively, which makes them complementary as considering a broader number of markets leads to improved representations of technological learning curves for battery prices. The key-steps of the iterative coupling are initiated by PTT-MAM feeding annual BEV and PHEV sales from Europe into TE3. After recalibrating the learning curves, TE3 is simulated and provides re-calibrated battery price curves for PTT-MAM. Convergence is reached after further iterations.

B.4. Other model combinations

Beyond the three groups summarized before, some other model coupling combinations have been found, which do not fit into those groups. Such approaches are described in the following sub-section.

One of the two model coupling approaches within this group that applies an ESM is by Millot et al. [83]. They apply a soft-linking method to combine economics, technology, and society. For this, they connect a statistical lifestyle model [109], the macroeconomic input-output model Metanoia [110], and the French TIMES ESM (TIMES-FR) [111]. The lifestyle model represents human behavior and is based on national surveys regarding household budgets, transport and journeys, housing, and the population census. It simulates demand pathways for the mobility, housing, services, and goods sectors on an individual level. The corresponding individual energy demands are given to Metanoia, which characterizes the relationships across the production sectors. Subsequently, the Metanoia model outputs (demands for freight-mobility, industry, services, and agriculture) and the lifestyle model results (mobility and residential demand) are fed to the TIMES-FR energy system model. In essence, this approach allows testing the impacts of varieties in different lifestyles dimensions, such as mobility practices and leisure travel preferences, within the society on the energy mix and emissions. However, this coupling approach does not consider any feedbacks, such as considering the impact of a carbon tax or changed fuel price on the reaction of consumers in the lifestyle model.

The second approach within this group that applies an ESM is developed by Steck et al. [84]. They soft-link the ESM REMix [96] with the charging model CURRENT [94] that represents the dynamic charging demand of *E*-vehicles by accounting for the decision algorithm of consumers, which is based on market mechanisms and charging preferences. Such charging behaviors are based on a real-world vehicle diary of PHEVs and BEVs. Due to the low number of such cars on the road, the corresponding information about charging behavior and charging preferences is a limitation of this study. Both models are coupled without taking a feedback loop into account.

Brand et al. [37] developed the United Kingdom Transport Carbon Model (UKTCM), which allows taking individual consumer behavior into account by hard-linking the four models [91], namely a Transport Demand Model (TDM), Vehicle Stock Model (VSM), Direct Energy and Emission

Model (DEEM), and Life Cycle and Environmental Impact Model (LCEIM). The TDM and VSM contain a feedback loop to reach a partial equilibrium. This allows taking into account the effects of changing consumer preferences and income and their influences on vehicle purchase decisions. The models also take exogenous scenarios into account that can describe changing attitudes and societal factors and can lead to changing numbers of future vehicles in the VSM. After TDM and VSM reached partial equilibrium, the number of traveled vehicle kilometers and the average trip distances, disaggregated by technology, vehicle age, and size to DEEM and LCEIM. DEEM calculates the direct emissions from the vehicle operation and provides such data to LCEIM. Finally, the LCEIM simulates the overall external costs and environmental impacts.

Mulholland et al. [85] aim to find the effects of financial stimuli for purchasing BEVs and PHEVs by hard-linking a socio-economic consumer choice model with 2 CarSTOCK models [89] for Denmark and Ireland, respectively. The socio-economic consumer choice model covers the private transport sector in a non-linear fashion and represents 18 heterogeneous consumer segments. It combines tangible costs for the consumer with monetized intangible costs, such as range anxiety, car model availability, refueling infrastructure, and risk-related disutility. The intangible costs are based on empirical data on consumer preferences of consumers. The two car stock models contain technological details for a high level of detail for available vehicle technologies. To hard-link these models, the socio-economic consumer choice model is applied first and provides market share trajectories for 15 private vehicle technologies to the CarSTOCK models. The CarSTOCK model calculates the coupling outputs regarding vehicle stock and activity, energy consumption, and CO_2 emissions.

Merven et al. [86] also aim to provide insights into the future vehicle stock and related energy demand by soft-linking five models: vehicle park model [112], Time Budget Model [86], CGE model [113], freight demand model [86], and fuel demand model [86]. Behavioral aspects are considered within the vehicle park, Time Budget, and CGE models. The vehicle park model differentiates vehicles by their annual mileage and age. The Time Budget Model limits the maximum traveling time to 1.1 h per person per day, while differing speeds of different travel modes and consumers of three different income groups that can therefore afford different transport modes. The CGE model provides inputs on the evolution of income groups based on GDP and population trajectories. Unfortunately, Merven et al. [86] neither outline which data are exchanged across the models nor in which order the models are applied, i.e., if the models run in consecutive order or all provide input data to the vehicle park model, for instance.

Mittal et al. [87] soft-link the global transport demand model AIM/Transport [114] that represents technology- and modal preferences of consumers with the global CGE model AIM/CGE [115,116] that applies MNL-type equations to reflect travel behavior. This coupling approach aims to find the impact of several factors on global travel demands, modal shares, and respective energy consumptions. Most of the factors examined in this study relate to mobility behavior, such as travel time, preferences for transport modes, socio-economic macro-developments, the occupancy rate of a car related to the per capita income, and environmental concerns. Data were only transferred from AIM/CGE to AIM/Transport without a feedback loop. Thus, effects from the behavior-oriented dynamics in AIM/Transport on other sectors of the energy system in AIM/CGE cannot be examined.

Appendix C. Overview of exchanged parameters between models in the reviewed model coupling approaches

Table 4
Overview of exchanged parameters between models in the reviewed model coupling approaches.

Source	Anable et al. (2012) [71]	Tattini et al. (2018) [72]	H. Daly et al. (2011) [73]	Mulholland et al. (2017) [74,75]	Wulff et al. (2020) [76]	Tattini et al. (2018) [77,78]	Girod et al. (2012) [34]	Schäfer & Jacoby (2005) [79]	Thiel et al. (2016) [80]	Blanco et al. (2019) [81]	Gómez Vilchez & Thiel (2020) [82]	Millot et al. (2018) [83]	Steck et al. (2019) [84]	Brand et al. (2012) [37]	Mulholland et al. (2018) [85]	Merven et al. (2012) [86]	Mittal et al. (2017) [87]
Vehicle price (purchase/operation)										✓							✓
Vehicle fuel efficiency	✓			✓				✓									✓
Fuel prices/energy prices						✓	✓	✓		✓							✓
Disaggregated consumer types					✓		✓										
Disutility costs [1]																	
Risk attitude																	
Vehicle make/model																	
Vehicle purchase numbers/vehicle market shares/vehicle capacity constraints	✓	✓	✓	✓	✓					✓	✓				✓		
Fuel consumption	✓				✓					✓			✓				
Emission targets										✓							
Demand forecast / Traveled distances		✓	✓		✓			✓		✓		✓		✓			
Modal Shares						✓		✓									
Income																	✓
Door to door speed																	✓
Car occupancy rate																	✓
Carbon tax																	✓
Not specified									✓							✓	

Note. The color coding refers to the combination of the model types that have been coupled following the four groups outlined in Section 2.2. Blue: Vehicle choice transport model and ESM; green: Modal choice transport model and energy (system) model; yellow: SD model and ESM (or another SD model); grey: other model combinations.
[1]Disutility costs include lack of charging/refueling infrastructure, range anxiety, lack of car-model availability, inconvenience, or lack of awareness.

Appendix D. Advantages and challenges of model coupling

The advantages of applying model coupling approaches can be manifold. A high-level research perspective has recently highlighted the importance of such multi-model analyses for supporting climate policies [166]. Most importantly, each involved model can retain its core purpose and characteristics, while the combined models can together still consider a broad set of aspects like consumer behavior. Thus, each involved model can facilitate its strengths when analyzing cross-cutting aspects. When new aspects shall be considered, they can be integrated into the most suitable model. Also, not every single output of one model must be passed on to the next model. Thus, models can contain different degrees of detail for certain aspects, which allows the combination of models to achieve more facetted results than a single model. Moreover, the linked models can be applied iteratively to consider dynamic feedback loops [72]. While such feedback loops require more complex data exchange processes between the models, this is rewarded by more robust and deeper insights into the transport dynamics and potential rebound effects that the combined models can deliver. Ideally, such iterations are stopped when a threshold in terms of changes in key parameters between consecutive simulations is reached.

Challenges of model coupling start with the initial need for data harmonization to achieve consistency across the involved models [166]. The models must be harmonized regarding existing input and output variables, assumptions, and system boundaries. It might seem trivial on the first view, but we emphasize the importance of thoroughly doing this at the beginning of the coupling project to avoid problems later. If this is not done correctly, the outputs of the involved models are not comparable, and errors from one model can cascade to others.[17] The need for harmonized data includes the granularity of time and space and the existing technologies covered within each model. Such data harmonization challenges typically occur when previously existing models are linked because they often have different scopes and system boundaries. To avoid such discrepancies, it would be ideal to couple models that are intentionally built together from scratch to link them, such as [131]. However, it is often not possible to build new models from scratch for practical reasons. Therefore, we recommend developing a mapping algorithm for all dimensions exchanged between the models. Wulff et al. [76] demonstrate an excellent example of applying different harmonization techniques to meet the requirements for each model dimension; unfortunately, their publication does not state clearly which data are exchanged across the model chain.

Another challenge in model coupling is that data from one model can induce infeasibility in the linked model. Alternatively, it can occur in iterative coupling approaches that the results of the models do not converge but, for instance, oscillate dynamically with each iteration. In such cases, it may help to either decrease or increase the degree of freedom between the linked models to achieve converging results. This can be done by determining a higher or lower number of outputs from one model that serve as inputs for the other model or by adapting the flexibility within each model.

A challenge that might be easily overlooked but can be crucial for the success of model coupling lies in the scientific background of the involved modelers. As a separate modeling team often develops each model, those teams may have different scientific backgrounds and scientific terminologies. Therefore, we recommend for the beginning of each project to develop a shared terminology that helps avoid communication problems and misunderstandings later. This can be a part of the data harmonization and model mapping exercise.

When the involved models come from different collaborating modeling teams, another common challenge can be that the access to the coupled model vanishes once the collaboration comes to an end. It is essential to consider how each model can be applied and developed independently afterward in such cases.

Drawing upon our extensive review of the literature, we summarize some best practices for successfully performing model couplings:

1. Define the aim of the coupling and select suitable models, which can fulfill the aim.
2. Establish a common and shared communication language across the modelers and define the meaning of important terminologies.
3. Develop a mapping algorithm for all relevant data dimensions in the models: determine the connection points between the models, i.e., which outputs from the one model serve as a valuable and relevant input for the other model, and vice versa.
4. Harmonize the data across the models (including spatial/temporal scope and resolution, base year calibration, assumptions for future technologies, policies, societal developments).
5. Create fixed templates for exchanging data between the models to enable automation processes.
6. Fix the future pathways/scenarios that will be analyzed and define which parameters in the involved models will be affected.
7. Identify potential lock-in effects that could occur when the models are coupled. Preventively, find ways for overcoming such lock-in effects (e.g., by adapting the degree of freedom between the models).
8. Apply iterative simulations to ensure considering feedback loops across the involved models. For this, determine a convergence threshold to stop the iterations. If no convergence can be reached, go back to point 4.

Overall, a careful trade-off between the possible advantages and the involved challenges is important. Mainly, model coupling allows additional insights from different perspectives on a given topic, such as the future of mobility, and avoids single models becoming highly complex to be handled. However, attention should be paid to choosing models with scopes that complement each other in utilizing their individual strengths and generating novel insights with the combined approach.

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