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Lifestyle change modelling for climate change mitigation: Complementary strengths, policy support, and research avenues

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ABSTRACT

Lifestyle changes are an essential, complementary measure for reducing greenhouse gas emissions and, therefore, also an important ingredient to climate policy. Computational models of lifestyle changes and their contribution to climate change mitigation can provide valuable insights in support of decision-making by individuals and policymaking. In this Perspective, we examine four modelling approaches with this in mind: input-output analysis, life cycle assessment, integrated assessment models, and agent-based models. They have different strengths and weaknesses related to spatial and temporal scales, sector representation, consumer heterogeneity, and impact assessment. Despite their differences, all are ultimately suitable for modelling different types of climate-friendly lifestyle changes – from sufficiency over efficiency to modal shift measures. Each modelling approach provides useful, albeit partial, insights into lifestyle changes. The identified challenges call for both continual refinements within individual model frameworks and hybrid methods that bridge their respective strengths and allow for representing lifestyle changes more comprehensively. Together, they inform about the theoretical mitigation potential, initiative feasibility, behavioural plasticity, and policy effectiveness of lifestyle changes. Ultimately, cross-disciplinary collaboration will be key to designing lifestyle-focused policies that are both impactful and acceptable.

1. Introduction

Lifestyle changes, i.e. changes on the demand side, are increasingly recognised as essential to a pathway to reach the 1.5°C target. Decarbonisation on the supply side alone cannot reduce greenhouse gas (GHG) emissions sufficiently (Cap et al., 2024), and heavily relying on carbon dioxide removal entails various risks and uncertainties (Rueda et al., 2021). Since lifestyle changes similarly affect domestic and imported goods, they avoid potential carbon leakage (Girod et al., 2014). Moreover, climate-friendly lifestyle changes often yield co-benefits for human well-being (Creutzig et al., 2022a), further supporting their importance.

While individuals can make lifestyle changes independently, they may encounter considerable barriers, some of which are structural in nature (Hirth et al., 2023; Vadovics et al., 2024). Lifestyles are shaped and constrained by the broader systems in which people live, such as infrastructure and economic incentives. Policy interventions can address these structural barriers and reshape systems to create more supportive environments that make lifestyle changes more accessible. In addition, the need for lifestyle changes and the effectiveness of some specific

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lifestyle changes also depend on the production systems satisfying consumer demands (Cap et al., 2024), and policies can support changes in such systems.

In our complex world, computational models have the potential to support policy processes regarding lifestyle changes. They can have a place throughout the different policy stages, such as policy design through target setting and exploration of policy options, as well as evaluation of implemented policies through impact assessment (Gilbert et al., 2018; Süsser et al., 2021). By enabling experiments in a virtual world, they offer several advantages over running "real-world experiments" or policy pilots: they save time and costs, avoid irreversability, allow to explore several alternatives under otherwise equal conditions or the same policy under different contexts, avoid ethical issues of administering a beneficial policy to some individuals but not others, and allow to examine possible futures (Gilbert et al., 2018). However, lifestyle change has so far been represented in models only to a limited extent, ranging from limitations in how models are constructed (Cian et al., 2020) to their representativeness and use in multi-scale policymaking (Filatova et al., 2025; van den Berg et al., 2019). These limitations hinder our understanding of the potential and scope of lifestyle change to support climate policy.

In this Perspective, we examine four distinct model families that are relevant to emulating anticipated impacts of climate-friendly lifestyle changes and are widely used in climate change mitigation research and policy-relevant applications: input-output analysis (IOA) (Tukker et al., 2020), life cycle assessment (LCA) (Jegen, 2024), integrated assessment models (IAMs) (van Beek et al., 2020), and agent-based models (ABMs) (Castro et al., 2020). Earlier articles have qualitatively compared different sets of model families for different scopes. For example, Boulanger and Bréchet (2005) compared six model families for policymaking in sustainable development, with a closer look at energy, land use, and transport, and the only overlapping model family were ABMs. More recently, Filatova et al. (2025) compared three model families on bridging decision scales for policy analysis related to climate change mitigation and adaptation, addressing global (IAM), economic (CGE) and agent-based modelling (ABM). Both of them focused on the supply side. In contrast, we zoom in on lifestyle changes and their representation across model families, which so far have received much less attention in climate change modelling and policies.

Modelling lifestyle changes is a field of innovation and a challenge for each of the modelling communities. A lack of oversight on this challenge across different modelling approaches obscures progress. It also remains unclear which modelling approaches are best suited to analyze specific challenges and how different paradigms can be bridged. The Perspective emerged from a day-long workshop featuring extensive discussions on the subject among modelling experts from various disciplines from both academia and boundary organisations. In the following, we highlight the models' strengths and weaknesses, their feasibility of modelling the contribution of different lifestyle changes to climate change mitigation, and the potential utilisation of such information for supporting policy processes, next to discussing new research avenues.

2. Model comparison

This section compares the attributes of four model families relevant to lifestyle changes:

– Input-output analysis (IOA), more specifically when linking to climate change mitigation environmentally extended IOA, is based on a demand-driven paradigm and attributes upstream environmental pressures to final demand by tracing inter-industry and interregional transactions usually in monetary units (Leontief, 1970). IOA uses data from national economic (and environmental) accounts (Tukker et al., 2020).
– Life cycle assessment (LCA) evaluates the environmental impacts of product or service systems across all life cycle stages by tracking the physical flows of resources and emissions from unit processes to the final functional unit (Hellweg and Milà i Canals, 2014). It follows guidelines under ISO 14040/14044 standards.
– Integrated assessment models (IAMs) integrate multiple sub-models or modules representing climate, land use, and energy system dynamics, which interact with economic and technological components to capture feedback effects (IAM Consortium, 2025). Most IAMs are driven by cost optimisation within a general equilibrium framework and assume market equilibrium and rational decision-making.
– Agent-based models (ABMs) simulate individual agents' behaviours and interactions through a set of equations, 'if-else' rules, and interactions with markets or other institutions to understand emerging macro-level phenomena (van Dam et al., 2012). Within the complex system science modelling methods, ABMs are considered the most suitable technique to represent complex human behaviours (Borshchev and Filippov, 2004; Walzberg et al., 2021). ABMs can represent decision-making through heterogeneous preferences, bounded rationality, cognitive processes, habituation, and social influence rather than assuming perfect rationality, equilibrium, or optimisation.

The four model families differ greatly, as do their strengths and weaknesses. IOA and IAMs are both top-down models, providing comprehensive pictures and macroeconomic insights based on their high spatial (often global) and sectoral coverage. Among these, IOA has the advantages of higher spatial and sectoral resolutions. In contrast, LCA and ABMs are bottom-up models, favouring depth over breadth. LCA offers process-specific insights at a much higher resolution. However, typically, inventory data only represent a specific region and major exporters, and only one or a few entities of a sector are represented in a given study. Similarly, ABMs typically focus on small scales like a community or city in great detail, with a focus on attributes relevant to agents' decision-making.

While IAMs and ABMs are dynamic models, IOA and LCA are typically static models. IAMs are used to assess long-term scenarios, often up to the year 2100 with an annual or 5-yearly resolution. Dynamic interactions are endogenously modelled through price-based decision-making. Similarly, ABMs capture dynamic feedback effects, allowing behaviours to emerge endogenously and diffuse across populations. Their decision-making processes are more complex and consider multiple criteria. Temporal coverage and resolution are flexible, as models are often custom-built (Crooks and Heppenstall, 2012). For example, EV-charging behaviour can be simulated hourly over the course of a month, while renewable energy technology adoption can be simulated yearly over decades. In contrast, IOA assumes fixed production recipes through technical coefficients (Miller and Blair, 2009). IO databases are constructed for specific years, often with some delay due to data collection efforts (Kitzes, 2013). LCA also works with fixed technical coefficients and is typically even time-agnostic, often assessing impacts under assumed current conditions. In both cases, dynamics can only be considered through exogenous perturbation.

ABMs excel in the simulation of heterogeneous agents. For the other model families, final consumer heterogeneity is limited. Heterogeneous consumption patterns have to be defined exogenously. Depending on the model and sector, some demographics, such as income groups or rural and urban, are distinguished in IAMs (Daioglou et al., 2012; McCollum et al., 2018). Similarly, some recent IOA research has disaggregated final demand into income groups or other socio-economic categories (Ivanova et al., 2017; Ottelin et al., 2019; Scherer et al., 2018; Zheng et al., 2022). LCA has similar limitations in that it typically only models the average consumer within a country rather than individual behaviours, although LCA can compare consumer archetypes such as different consumption patterns, income groups, or urbanisation levels (Froemelt et al., 2018; Nita et al., 2017).

IOA, LCA, and IAMs can all assess GHG emissions comprehensively. Climate change mitigation scenarios are a common application of IAMs (Guivarch et al., 2022; van Beek et al., 2020). LCA considers a wide range of environmental impact categories well beyond GHG emissions, and it is common to assess trade-offs among impact categories (Guinée, 2015). While environmentally extended IOA traditionally focuses on GHG emissions, several recent databases also allow for assessing a multitude of environmental impacts (Stadler et al., 2018).

3. Applicability of models to lifestyle change analyses

Lifestyle changes are reflected in altered consumption patterns and can take various forms. They are commonly categorised as *Avoid* (e.g., reducing travel), *Shift* (e.g., transitioning to public transport), or *Improve* (e.g., adopting more efficient electric vehicles) (Creutzig et al., 2022a). They can also be distinguished by whether a change requires, above all, a financial investment (e.g., insulating the house) or an actual behaviour change (e.g., changing your diet) (Vadovics et al., 2024). Such different categories of lifestyle change impose different requirements both on individuals implementing them and modellers.

Lifestyle changes cannot be directly modelled in IOA, but IOA is often used to assess the effects of a change in final demand (Wood et al., 2018), which can be used as a proxy for a change in lifestyles. *Avoid* measures are straightforward to model, as they simply require reducing the final demand when disregarding potential re-spending of the saved expenditure. The ease of modelling *Shift* measures depends on the required product resolution and the ease of converting between monetary and physical units to determine an appropriate level of substitution. It can, therefore, range from high for simple shifts in final demand categories to low for the necessity of detailed adjustments in the technical coefficients to reflect new production recipes. *Improve* measures are again relatively easy, as they require reducing the final demand for energy or adjusting the emission coefficients. The only tricky part is adjusting direct emissions from households, which aggregate emissions from cooking, heating, and mobility.

LCA is best suited for evaluating the environmental impacts of discrete lifestyle changes that involve multiple alternatives producing the same function, such as shifting to low-carbon transportation or adopting more sustainable diets (Nita et al., 2017). LCA can also assess how technological advancements and fuel mix changes influence environmental outcomes by comparing the model's output with each technology change. So, both *Shift* and *Improve* measures can be captured well. For *Avoid* measures, the effectiveness can best be assessed in relation to the overall footprint of an individual, which is more difficult based on LCA. Moreover, neither conventional IOA nor LCA can represent dynamic individual decision-making.

IAMs have traditionally been able to represent *Shift* and *Improve* measures more structurally in their model formulations given some level of economic incentivisation that can be attributed to such measures (van den Berg et al., 2019). Examples are shifting transport mode (Girod et al., 2013), vehicle choice (McCollum et al., 2018), recycling behaviour (Daioglou et al., 2014; Stegmann et al., 2022) and housing (van Heerden et al., 2025). Accounting for *Avoid* options has been more challenging, although recent efforts have worked to represent their effects in IAMs. These measures are mostly captured through proxies, e.g. exogenously via narratives or stylised through changes to calibration factors (van den Berg et al., 2024; van Sluisveld et al., 2016). Lifestyles are then mostly implemented in a linear fashion, replicating the original (rational economic) decision-making response, just with newly set constraints or intensities of activities. As dynamic models, they can also reflect decision-making to some extent; however, changes that require mainly a financial investment are easier to simulate due to the price-based decision-making in IAMs.

Overall, IOA, LCA, and IAMs are suited to measure the GHG emissions of lifestyle changes, but not *who* is making the change or the rationale behind it (Madsen and Weidema, 2023). Also, none of them can capture social interactions that are relevant to understanding lifestyle changes. In contrast, ABMs offer the possibility to simulate heterogeneous agents, interactions among them, and decision-making beyond prices as a criterion. This makes them especially well-suited for modelling actual behaviour changes and could lead to an understanding of adoption conditions for lifestyle change. ABMs can also be employed to track the effects of individual lifestyle changes over time focusing on specific behaviours such as energy use, mobility, and product consumption (Ribeiro-Rodrigues and Bortoleto, 2024) and holistic lifestyle changes considering spillover (Allen et al., 2019).

4. Suitability of models for supporting policymaking

Here, we elaborate on modelling contributions to three essential dimensions of lifestyle change for emissions reductions – theoretical/technical mitigation potential, initiative feasibility, and behavioural plasticity (Nielsen et al., 2020) – that together inform policy effectiveness. This framework aims to be comprehensive and to address that an opportunity to mitigate climate change does not necessarily reach its full potential. Each dimension illuminates distinct policy-relevant questions about lifestyle changes and guides the selection or development of suitable modelling techniques.

4.1. Theoretical mitigation potential

IAMs, with their capability for dynamic scenario analyses and feedback loops among different submodels, are unique in that they can estimate the remaining carbon budget we can afford to remain under a certain temperature by the end of the century, such as the 1.5°C target established in the Paris Agreement. They are also used to simulate if we can get back to a temperature level after temporarily overshooting it. Comparing such a carbon budget to the annual global emissions indicates how much such emissions must be reduced overall.

Once such a global target is set, the next question is how the necessary reductions are distributed among different countries and consumer groups. Which approach for the distribution can be considered fair is an ethical question. However, whatever approach is chosen, it requires estimates of current and potentially even historical carbon footprints to account for cumulative GHG emissions to downscale the targets and determine the gaps to these targets. IOA is ideal for this type of analysis thanks to its comprehensiveness and the representation of at least the dozens of major economies as individual countries and has already been used for such purposes (Cap et al., 2024). As mentioned above, IOA, LCA, and IAMs can be employed to estimate the mitigation potential of numerous lifestyle change options. IAMs can also capture how multiple intervention strategies might interact, noting that their collective effect can be more complex than a simple sum of individual impacts (van Heerden et al., 2025). IOA, with its monetary units, can additionally account for financial rebound effects that can offset some of the mitigation potential (Hertwich, 2005). Only ABMs are not well suited to assess the theoretical mitigation potential.

4.2. Policy acceptance and initiative feasibility

Initiative feasibility involves evaluating whether a proposed mitigation effort can be implemented by governments and other actors in a way that yields effective results (Nielsen et al., 2020). For lifestyle-based transitions, structural support and collective action are crucial; hence, public acceptance is often the deciding factor (Chater and Loewenstein, 2023). Nevertheless, the literature focusing on stakeholder support and feasibility is comparatively sparse, leaving policymakers uncertain which instruments to prioritise (Nielsen et al., 2024).

Among the available modelling approaches, ABMs hold particular promise for incorporating insights from political science, such as preferences, negotiation dynamics, and policy acceptance (Savin et al., 2023). Recent work has, for instance, integrated households' preferences into global climate policy negotiations (Gerst et al., 2013) and investigated public support for carbon tax dynamics (Konc et al., 2022). Feasibility in IAMs has been studied mostly by computing multi-dimensional feasibility metrics derived from aggregated demand-side transformations and by comparing alternative decarbonisation pathways (Brutschin et al., 2021).

Another barrier to acceptance can be when policies have been evaluated with computational models due to low trust in outcomes from complex and difficult-to-understand models whose assumptions are hard to validate. Participatory modelling, in which stakeholders are involved early in the modelling process, can increase the chances that the model will be accepted and useful to policymakers (Gilbert et al., 2018). Stakeholders like policymakers can, for example, co-define the study scope, support making realistic assumptions in the model, and indicate which model outputs would be valuable (Süsser et al., 2021).

4.3. Adoption of lifestyle change and behavioural plasticity

Behavioural plasticity describes the fraction of non-adopters who can be induced to change their behaviour via interventions (Dietz et al., 2009). ABMs can simulate the decision-making processes of individuals and other stakeholders, accounting for both internal motivations and social influences, although not necessarily interactions with changing infrastructure over time. Thereby, ABMs shed light on lifestyle changes (Castro et al., 2020; Ribeiro-Rodrigues and Bortoleto, 2024). IAMs can include some of these behavioural dimensions, but typically in a highly aggregated manner, focusing on economic drivers (Mastrucci et al., 2023). Conventional IOA and LCA approaches generally treat behavioural plasticity as an external assumption (e.g., predefined adoption rates), constraining their ability to explore endogenous behavioural shifts (Koide et al., 2021).

4.4. Effectiveness of policies on emission reduction

Ideally, a policy would offer substantial mitigation potential, enjoy widespread public support, and present relatively few adoption barriers (Nielsen et al., 2020). Assessing the performance of a policy involves integrating the three perspectives discussed above, i.e. theoretical potential, feasibility, and behavioural plasticity.

Policies can be assessed retrospectively or prospectively using computational modelling (Gilbert et al., 2018). Conventional IOA and LCA are primarily retrospective, examining the impacts of existing or past policies. Although this backward-looking approach offers valuable lessons, it may not fully capture how future technological or behavioural changes could influence policy outcomes (Di Bari et al., 2024; Palazzo et al., 2020). In contrast, prospective analysis is a core strength of IAMs and ABMs, which can explore hypothetical scenarios, future policy impacts, and the complex interactions among sectors and actors.

A robust evaluation of policy effectiveness requires recognising the heterogeneity of behaviours and policy responses across individuals (Smith, 2022). Factors such as consumer preferences, socio-economic status, and cultural norms can lead to vastly different adoption rates and outcomes (Koide et al., 2025; Olson et al., 2024). IOA and IAMs typically approximate heterogeneity by segmenting consumers into broad categories. Meanwhile, ABMs allow a more fine-grained view by representing individual households, enabling the modeller to capture how specific subgroups might respond to policy incentives or structural changes (Chappin et al., 2017).

Another critical consideration is the set of policy instruments being analyzed. IAMs traditionally emphasise economic tools, such as carbon taxes or fuel mandates, assuming relatively rational decisions within fairly homogeneous groups (Trutnevyte et al., 2019). ABMs, in contrast, can simulate the decision-making processes of multiple stakeholders, from consumers to regulators, when exposed to a variety of policy levers, from subsidies to information campaigns (Castro et al., 2020; Ribeiro-Rodrigues and Bortoleto, 2024). However, ABMs can be hard to calibrate and typically do not quantify emissions. IOA or LCA can fill this gap and, jointly with ABMs, allow for evaluating the overall impact on GHG emissions (Micolier et al., 2019).

5. Promising research avenues

To further the development of effective scientific advice on lifestyle change in the environmental arena, we utilise the framework of Cash et al. (2003) to structure our recommendations. The framework defines the need for credibility, saliency, and legitimacy to create impact beyond the scientific realm (Cash et al., 2003). Traditionally, scientific knowledge actors have focused on trusted and believable information (credibility), though as important is to tailor the information to the end user (salience) and ensure inclusion of different value systems (legitimacy). To be able to understand and evaluate the potential of lifestyle changes to reduce GHG emissions much better, we propose three research avenues:

1) Credibility: The current models used for representing lifestyle changes need to be improved, especially regarding their credibility and reusability, which can be done within each model domain, perhaps borrowing from others.

2) Beyond credibility: A coupling of computational models is necessary to evaluate lifestyle changes from different angles and overcome the limitations of individual models by exploiting their complementary strengths.

3) Legitimacy: People's preferences and drivers of behaviour resulting in lifestyle changes need to be better understood and fed into the models, to which theoretical and empirical social science methods can contribute.

The following subsections elaborate upon each research avenue.

5.1. Credibility and reusability of lifestyle models

Credibility implies the scientific adequacy of representing lifestyles. Within the domain of IOA, LCA, IAMs, and ABMs, some common themes need more research and attention to enhance the models' credibility. While model validation based on observed data is often infeasible due to the unobservable nature of the models' results (e.g., a carbon footprint of a product or service system as modelled in LCA cannot be measured in practice), especially for prospective assessments, several steps can be taken to assess a model's adequacy and reliability (Randall and Ogland-Hand, 2023). For example, although not frequently done so far, in IOA and LCA, uncertainties can be assessed (Heijungs, 2024; Schulte et al., 2024). Others synthesise methods that can be used to evaluate IAMs (Wilson et al., 2021) and validate ABMs (Collins et al., 2024). Such assessments can also support identifying key areas that require further data collection or model refinement efforts to increase the realism of the models.

Transparency can also help build trust (Randall and Ogland-Hand, 2023), enable cumulative science (Pauliuk, 2020), and facilitate the development of integrated approaches (see next subsection). This seems especially helpful considering the relatively early stage of lifestyle change modelling. Open data and open-source models are important for this purpose. Several IO databases, such as EXIOBASE (Stadler et al., 2018), are publicly available, as is open-source code for conducting IOA (Stadler, 2021). LCA faces particular challenges in data transparency, as portions of the data often come from proprietary databases accessible only for a license fee and confidential data provided by companies, but a better balance between transparency and privacy could be achieved (Kuczenski, 2019). In contrast, multiple options for open-source LCA software are available (Ciroth, 2007; Mutel, 2017; Steubing et al., 2020). While transparency in IAMs has historically been limited (Skea et al., 2021), a movement exists to create openness around the models contributing to the latest IPCC report (e.g. the IAM wiki documentation; IAM Consortium, 2025). ABMs have a tradition of open-source models such as the CoMSES network and model library, which can also provide peer-review functions (Janssen et al., 2008). Nevertheless, most ABMs are still built from scratch rather than being reused, extended, or adapted by the research community. This is inefficient and results in many different implementations of the same behavioural theories, potentially creating issues of legitimacy as outlined in Section 5.3. A recent initiative promoting the reusability of ABMs is that of Reusable Building Blocks (Berger et al., 2024). The idea is that they describe individual mechanisms and processes on a generic level so they can be reused in various models. The Reusable Building Blocks can be found in an open repository. Apart from open data and open-source models, clear documentation of model assumptions, such as the (key) causal relationships of complex models like IAMs and ABMs, is valuable and helps understand the behaviour of the models. While there are widely followed protocols for describing ABMs and their empirical grounding (Grimm et al., 2006; Laatabi et al., 2018; Müller et al., 2013) that help make model descriptions more understandable and complete, this is only available for more aggregated levels in IAMs (e.g., in sophisticated platforms like the IAM model documentation), with details on the specific data and assumptions used usually scattered around in literature.

5.2. Beyond credibility: model coupling and learning across representations

Building a common knowledge base may be favourable for lifestyle change scholars, as "[c]redibility is hard to establish in arenas in which considerable uncertainty and scientific disagreement exists, either about facts or causal relationships" (Cash et al., 2003). As detailed above, the main models currently used for assessing environmental impacts differ considerably in coverage, resolution, and dynamics. Since each contributes fundamentally to the framing, implementation, and evaluation of policies to achieve climate targets, their hybridisation and combination offer promising research avenues.

The coarse product groups distinguished in IOA, as well as the potential lack of representativeness and process cut-offs from limited system boundaries in LCA, can hamper the analysis of lifestyle changes. Hybrid LCA, coupling IOA with LCA, instead can lead to a more comprehensive and precise analysis (Hagenaars et al., 2025). Also, IOA and IAMs complement each other, and the former could be used to increase the sectoral resolution of the latter (Malik and Schaeffer, 2024). In turn, IAMs can help create IOA models of future scenario worlds (Cap et al., 2024) and increase the robustness of prospective LCAs by considering future background system changes (Mendoza Beltran et al., 2020).

All three model families suffer from limited representation among actors, which ABMs can improve. For example, ABMs can represent the social dynamics between heterogeneous agents that adopt a specific behaviour or technology, creating a series of alternative scenarios. When coupling with LCA, the collective behaviour of these actors can, in turn, influence the technological development in specific production chains through changes in the technical coefficients. Actor behaviours can also influence consumption patterns through changes in the total demand for functional units or in the composition of products/services fulfilling those units in LCAs (Hicks, 2022; Micolier et al., 2019). Similarly, coupling ABMs with IAMs combines economy-wide dynamics with detailed modelling of behavioural diversity. Such an approach enables the representation and analysis of complex phenomena emerging across scales, including tipping points and nonlinear transitions in socio-economic systems (Lackner et al., 2025).

Even if not coupling models, it could still be valuable to use multiple models not only within one model family (van Heerden et al., 2025) but also across model families to check the robustness of the results.

5.3. Legitimacy: potential contributions of theoretical and empirical social sciences to modelling lifestyles

To model when, how, and if lifestyle change occurs requires a comprehensive representation of people's preferences and the drivers of people's behaviour (e.g., Schlüter et al., 2017; van Valkengoed et al., 2025). Different social science disciplines, including psychology (van Valkengoed et al., 2025), behavioural economics (e.g., Brekke and Johansson-Stenman, 2008; Mayer et al., 2023), political science (Newell et al., 2022) and sociology (e.g., Lockie, 2022) hold key insights that can inform the modelling of lifestyle changes in different ways.

Empirical work from the social sciences can be used to parameterise agents and determine decision rules for them in ABMs (e.g., Eker et al., 2019; Niamir et al., 2020; Schlüter et al., 2017; Scholz et al., 2023) or to introduce heterogeneity between actors in other ways, for example, by introducing different consumer groups in IOA (e.g., Ivanova et al., 2017; Koide et al., 2019) or IAMs (e.g., Edelenbosch et al., 2018; McCollum et al., 2017; Pettifor et al., 2024). The theoretical mitigation potential of lifestyle changes estimated through IOA or LCA can be further refined by empirically examining the behavioural plasticity of these changes, or people's ability and willingness to change their behaviour (e.g., Koch et al., 2024; Payró et al., 2024). Existing empirical data can also be used to validate models via hindcasting (e.g., Kaaronen and Strelkovskii, 2020). Social science methods can further be used to co-create scenarios, pathways, and models using participatory approaches such as workshops with stakeholders and interviews (e.g., Pedde et al., 2021; van den Berg et al., 2024; van Sluisveld et al., 2016; van Sluisveld et al., 2020; Vita et al., 2019; Wachsmuth et al., 2023). Particularly the influence of different narratives on each other has been considered relevant in this respect (Creutzig et al., 2022b).

Modellers can run into disciplinary barriers when employing the rich resources available in the social sciences. Theories in social science are manifold and not mutually exclusive, with varying foci and levels of analysis, which can make navigating the literature and selecting relevant theories challenging (e.g., Schlüter et al., 2017; van Valkengoed et al., 2025; Wijermans et al., 2023). Translating verbal descriptions of theories into models is also not straightforward and can reveal key uncertainties and ambiguities which require modellers to make critical decisions on how to best represent theoretical propositions (e.g., Muelder and Filatova, 2018; Schlüter et al., 2017; Taraghi and Yoder, 2025). Empirical research results in the social sciences are often heterogeneous, and distiling key outputs or parameters can be challenging (Linden and Hönekopp, 2021). Through more intensive collaborations, social scientists can help modellers overcome these challenges to ensure this literature is used most effectively and is accurately represented in modelling applications (de Vries et al., 2021; Elsawah et al., 2020; Trutnevyte et al., 2019; van Valkengoed et al., 2025). In addition, collaborations can ensure empirical work is more closely coupled to specific modelling applications.

6. Conclusions

As underscored throughout this Perspective, lifestyle change representations and effects are analyzed across multiple research fields. Despite sizable corpuses in these fields underscoring the importance of lifestyle change as a favourable intervention to combat climate change, they are far from addressing lifestyle change holistically. Snippets of its driving force or effects can be obtained from specific modelling paradigms and scientific disciplines, though these empirical bases are still very much in development as a science and in their practice. In general, it is understood that knowledge of causation and correlation can be drawn from historical phenomena, expert elicitation or surveys, though such empirical evidence may not immediately find further application in models on impact assessment yet. Further experimentation and integration are therefore considered important to better understand these fundamental mechanisms that motivate personal choice over time and space and what that means for the global socio-ecological and socio-economic systems. Interdisciplinary collaboration is still not the standard – disciplinary evaluation criteria disincentivize the various schools from more thoroughly collaborating, and difficulties due to different languages and working styles may reduce productivity. However, sharing common goals and showing mutual trust and respect can increase the group's effectiveness and lead to innovative research (Specht and Crowston, 2022) capable of addressing complex sustainability challenges such as climate-friendly lifestyles more holistically.

The literature on lifestyle change can contribute to many facets relevant to a more systemic societal change. However, as outlined above, recent efforts appear to have mostly evolved around improving credibility and legitimacy, making it a rather isolated scientific endeavour of modelling and social science communities. Considering also the tension between translating knowledge to actual action (Dechezleprêtre et al., 2025), engaging more with stakeholders and decision-makers in scoping and developing knowledge can improve the salience of the research field. Such more holistic assessments may offer greater value for agents of change and those in positions of power.

CRediT authorship contribution statement

Laura Scherer: Writing – original draft, Conceptualization. **van Sluisveld Mariësse A. E.:** Writing – original draft, Conceptualization. **Nicole J. van den Berg:** Writing – original draft. **Stephanie Cap:** Writing – original draft. **Agnese Fuortes:** Writing – original draft. **Lynn de Jager:** Writing – original draft. **Ryu Koide:** Writing – original draft. **Arjan de Koning:** Writing – original draft. **Giacomo Marangoni:** Writing – original draft. **Francesca Rubiconto:** Writing – original draft. **Anne M. van Valkengoed:** Writing – original draft.

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Data availability

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

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