A conceptual validation of the Consumer Choice Framework

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Abstract. The global energy transition is a complex challenge that requires innovative research approaches. Understanding individual decision-making is crucial, as local investment decisions and the operation of such acquired assets will shape the future energy system. Agent-based models (ABMs) are widely used to simulate individual energy behaviors and interactions. In this paper, we adopt the Consumer Choice Framework[1]—a metamodel that provides an abstract reference architecture for integrating psychological, social, and economic dimensions of energy behaviors. This metamodel is designed to foster interdisciplinary collaboration by offering a shared language across research domains. We validate it by mapping it to three existing ABMs, demonstrating its value as a shared reference framework.

Keywords: agent-based modeling, consumer choice metamodel mapping, interdisciplinary collaboration

1 Introduction

The global energy transition is a multifaceted challenge that demands innovative and interdisciplinary research approaches. More specifically, understanding individual decision-making in this context is key to a successful transition: local investment decisions (i.e. in rooftop PV, storage, heating technologies, and mobility), along with energy demand behavior and asset operation will shape the future energy system [29,20]. Agent-based models (ABM) have emerged as a powerful tool for simulating individual behaviors and interactions within the energy system, offering insights into how micro-level actions influence system-level outcomes [19,14,15]. However, ABMs are more effective in capturing these dynamics when they incorporate perspectives from multiple disciplines. Individual energy demand is shaped by an interplay of internal (e.g. risk perception, affect) and external (e.g., norms, policies) factors [4], underscoring the need for interdisciplinary energy behavior modeling. Integrating knowledge from psychology, sociology, economics, and engineering remains challenging, as each discipline brings distinct terminologies, assumptions, and modeling paradigms [6]. This disciplinary fragmentation often hinders effective collaboration and limits the development of integrated, policy-relevant tools.

Building on prior research in energy-related consumer behavior [7,?], we adopt a Consumer Choice Framework that serves as a metamodel integrating psychological, social, and economic factors to support interdisciplinary modeling and foster a common language across disciplines [1]. In this paper, we focus on the conceptual validation of this metamodel. We assess its generalization in this domain and integrative capacity by mapping it onto three existing ABMs. Through this mapping, we demonstrate the framework's potential to unify model design and support interdisciplinary collaboration in behavioral energy modeling.

2 Related work

2.1 Frameworks for decision-making

Agent-based models (ABMs) are widely used to simulate individual decision-making across social layers and domains [3,30,14,5]. Their flexibility enables diverse, discipline-specific implementations. Interdisciplinary frameworks underscore the importance of justifying model fit in social-ecological systems and systematically comparing behavioral theories [33,25]. Meta-frameworks aim to integrate behavioral theories into ABMs. Examples include Consumat [13], where agents adopt different decision strategies (e.g., repetition, imitation) depending on their satisfaction and uncertainty levels, and HUMAT [12], which extends this approach by incorporating socio-cognitive mechanisms such as motivation and social influence. The CAFCA [8] is a framework for modeling context-dependent agent decision-making in social simulations, while MoHuB [26] supports mapping and comparing behavioral theories in social-ecological models. To facilitate abstract interdisciplinary communication and model comparison in ABM design, we adopt the metamodel [1] due to its theory-agnostic nature, minimal restrictions on the design space and alignment with domain-specific requirements.

2.2 Approaches for Inter-Model Comparison and Interdisciplinary Communication

To our knowledge, no metamodel currently supports interdisciplinary communication in ABM design. Related concepts, such as the ODD protocol [9,10], enable detailed model documentation and comparison. However, the complexity of the ODD protocol limits its use for abstract, cross-disciplinary dialog. Comparable efforts demonstrate how structured frameworks can bridge disciplinary divides. For instance, the Toolkit of Interdisciplinary Energy [18], applied to the development of small-scale solar photovoltaics in Greece, supports the design

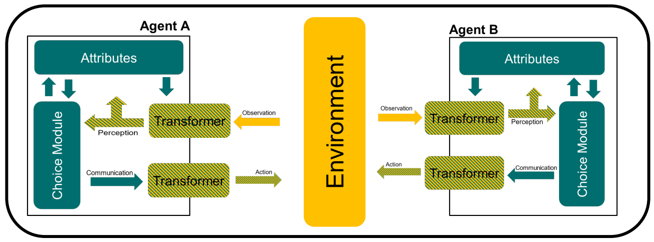

Fig. 1. Overview of the model framework[1]

of adaptive policy pathways by incorporating various stakeholder perspectives. In consumption studies, the Transdisciplinary Consumption framework [17] enhances the understanding of consumer behavior by integrating insights across disciplines. Likewise, a comprehensive transdisciplinary theoretical framework for citizen science seeks to unify diverse academic perspectives and improve the understanding and implementation of citizen science initiatives [27]. Collectively, these examples aim to transcend disciplinary boundaries by enabling shared conceptual understandings and harmonizing terminology across fields.

3 Consumer choice framework description

The metamodel was developed in an interdisciplinary project to unify agent-based modeling of consumer behavior in energy systems, offering a shared conceptual structure for collaboration (see Consumer choice framework: Reference architecture [1] for details). It comprises two main components (Figure 1): agents—representing decision-makers like consumers, households or enterprises—and the environment they interact with. Agents perceive and act upon environmental information, creating a bidirectional flow that shapes both behavior and context. The following sections detail each component.

3.1 Environment

The environment serves two major purposes: it provides information about the physical properties and possible futures of the modeled world, and it enables agent communication. The environment consists of five main components, which may interact with each other in varying degrees of complexity:

- *Physical assets* describe the availability of resources, technologies, and installations. In energy, examples include natural resources like wind and solar power, heating technologies, and infrastructure such as electricity grids.
- *Exogenous processes* detail the external behavior of environmental aspects over time, such as weather conditions affecting resource availability or long-term processes such as technological progress, disruptive events, and crises.

- *Knowledge assets* refer to immaterial assets that is information available in the environment. Such information evolves either endogenously through information created by agents and communicated to the environment or exogenously through some predefined processes.
- *Networks* are groups of agents interacting in various forms, from bilateral physical interactions to open networks where agents share information, often via media channels. They also include societal and administrative structures like neighborhoods and municipalities.
- *Rules of interaction* specify agent interactions shaped by cultural, legal, and market contexts.

3.2 Transformers

Agents interact with their environment by receiving and sharing information. The environment contains all information that is publicly available or communicated. When agents take in information or share it, it is transformed into their subjective understanding. This transforming defines the boundary between the agent and the environment.

The model includes two transformation processes. Filtering limits what information is available to the agent, often based on their social networks or media exposure. For example, an agent might only receive information from familiar sources such as local communities or subscribed media channels.

Distortion alters or suppresses information influenced by agent attributes. Perception can be shaped by motivated reasoning, where information is interpreted in belief-consistent ways. Communication to the environment can be influenced by social approval, personal goals, or external pressures. Importantly, filtering and distortion are closely linked. Agents shape their informational environments, for example, by selecting belief-aligned sources or networks, which reinforces filtering (through selective exposure) and distortion (through biased interpretation). Cognitive biases such as confirmation bias typically involve both processes.

It is important to note that objective information in this context refers to information made available but does not necessarily reflect an absolute or global truth. For example, an agent might decide to vote against an energy law while publicly claiming to have voted for the law. In this case, the environment contains two conflicting signals: the anonymous vote, and the agent's intentionally distorted communication.

3.3 Agents

Agents represent entities such as individuals, households or firms. They receive information from the environment, which is filtered and possibly distorted. The agents' behavior is defined by the choice module (see Figure 2).

- *Attributes* are internal factors influencing agent behavior through event triggers, evaluations, and aggregation. Variations in agent attributes—such as

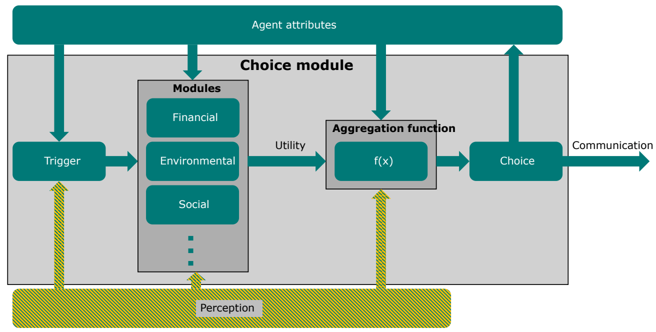

Fig. 2. Agents' choice module [1]

age, income, or norm sensitivity—lead to different choices. Attributes may evolve through decisions or autonomously (e.g., EV adoption changes car ownership; age changes autonomously). We group them into psychological, socio-economic, and stock variables.

- The *choice module* is at the core of the consumer framework. Based on attributes and perceived information, the agent makes choices.
  - *Trigger* listens for and reacts to predefined events that initiate the agent's decision-making process. In the absence of such an event, the agent does not engage in decision-making. The exact triggers depend on the modeled behavior, and there can be multiple trigger events for a specific behavior.
  - *Evaluation dimensions* specify which fundamental values influence the decision-making. These could include financial factors (e.g., investment costs), environmental factors (e.g., environmental footprint), social factors (e.g., social norm), and any other factors selected by the modeler.
  - *Aggregation function & Final choice*: The choice component compares the aggregation function's value across alternatives to determine the final choice. Examples include threshold utility maximization functions.

These components draw on the agent's attributes and perceptions, while choices can alter attributes and influence the environment (see Figure 2).

4 Model mapping

This section presents the mapping of the metamodel to three independently developed ABMs in the given domain. The mapping supports the metamodel's role as a communication facilitator in interdisciplinary ABM development for consumer choice. The following subsections briefly describe the models and their mapping to metamodel concepts, as shown in Table 1.

4.1 Mapping: SEED

The Socio-Economic Energy model for Digitalization (SEED) is an agent-based model developed to analyze the impact of digitalization-induced social practices,

Table 1. Metamodel, BedDeM, Co-adoption model and SEED Concepts Mapping

	Metamodel	**BedDeM**	**Co-adoption**	**SEED**
Agent	Attributes	Memory	Psychological attributes Socio-economic attributes Stock variables	Socio-economic attributes Preferences Stock variables
		Trigger		
	Choice module: Trigger Evaluations Aggregation Choice	Decision-making: 1st level 2nd level Last level Choice	Choice module: Trigger events Evaluation Aggregation Threshold model	Choice module: Events Utility function Weighted sum Adoption of practices/technologies
Environment	Physical assets		Technologies	Technologies & Infrastructure
	Exogenous processes	Tech. & Social evolution	Learning rate prices	Tech. cost & energy price evolution
	Knowledge assets	Opinion channels		Awareness of practice & technology
	Networks	Social networks	Location between agents & neighbors	Social networks
	Rules of interaction		Opinion sharing	Social influence rules
Transformers	Incoming: Filter Distortion	Incoming: Perception	Incoming: Opinions from neighbors	Incoming: Perception of options Behavioral biases
	Outgoing: Filter Distortion	Outgoing: Communication	Outgoing: Opinions to neighbors	Outgoing: Selective sharing Modified energy demand

such as teleworking and e-commerce, on the Swiss energy transition towards net-zero carbon dioxide emissions by 2050 [28].

The SEED model simulates agents' decisions on adopting digital practices and low-carbon technologies, with information flowing between agents and their environment through social interactions and energy system feedback. The basic concepts of SEED are summarized in Table 1, contrasting the metamodel concepts from Table 1 with SEED's architecture. The mapping positions SEED's components based on their function within the metamodel reference framework. The *attributes* in SEED include socio-economic factors (e.g., age, income), preferences (e.g., environmental awareness), and stock variables (e.g., technology ownership), stored within each agent to represent heterogeneity. The *choice module* is a multi-criteria decision function, where *triggers* (e.g., infrastructure availability) initiate *evaluations* based on cost, preference, infrastructure, and market components. These are *aggregated* in a weighted sum, leading to choices like adopting teleworking or electric vehicles. The *environment* encompasses physical assets (e.g., EVs, heat pumps), exogenous processes (e.g., technology cost reductions), knowledge assets (e.g., awareness of digital practices), social networks driving interactions, and rules governing social influence. *Transformers* filter and distort incoming information (e.g., network-based perception) and outgoing actions (e.g., adjusted energy demand sent to STEM[24]).

4.2 Mapping: BedDeM

The Behavior-driven Demand Model (BedDeM) has been used for modeling modal choice and vehicle purchasing choice [22]. The main components of the agent's decision-making process are shown in Figure 3. The perception compo-

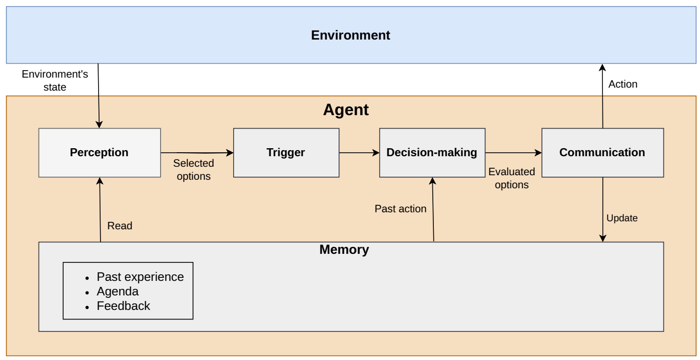

Fig. 3. Agent model in BedDeM[21]

nent observes information about available options in the environment and filters and sorts them, compiling a shortlist of options. Whenever the agent's internal state, stored in the agent's memory, or the created shortlist of options satisfies specific criteria, the *trigger* component triggers the decision-making process. The decision-making process is based on Triandis' theory of interpersonal behavior (TIB) [2]. The available options are evaluated based on utility values [23] and the best option is selected. The output is sent to the environment with the Communication component and the Memory component of the agent is updated accordingly. The basic concepts of BedDeM have been summarized in Table 1 contrasting the metamodel concepts. As shown in Table 1, the *attributes* are stored in the memory and the *choice module* is a decision-making component based on the TIB theory. The environment's *exogenous processes* are the technical and social evolution of the agents. *Knowledge assets* are represented as opinion channels, which were used for the EV adoption based on the car reviews. *Networks* are social networks between neighbors based on the location.

4.3 Mapping: Co-adoption of low-carbon household energy technologies

The *Co-adoption of Low-carbon Household Energy Technologies* model simulates the diffusion of solar panels, electric vehicles, heat pumps, and home batteries in Swiss households [32,31]. The model is grounded in psychological theory [16] and empirical survey data. It simulates individual adoption decisions for each technology, as well as the decision to co-adopt multiple technologies. The agents' decision-making processes follow the risks-as-feelings framework [16] as illustrated in Figure 4. The agents in the model are individual households, with social

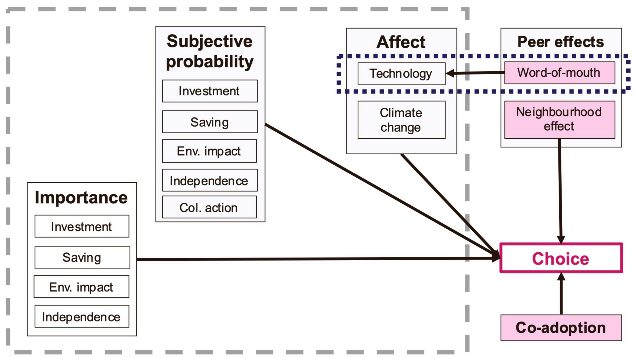

Fig. 4. Decision-making model Co-adoption of low-carbon household energy technologies as presented in [32]

interactions established between agents and their closest neighbors. Households *interact* via direct word-of-mouth communication and are influenced through indirect neighborhood effects (social norms). *Agents' attributes* include demographic and psychological characteristics, such as home ownership, or attitudes toward technologies. Adoption decisions are *triggered* when the technologies' ages reach their replacement time or lifetime. Barriers to adoption are technology-specific (e.g. heat pump adoption is restricted for tenants). Adoption decisions follow a *threshold model*, where agents adopt if the utility of adoption exceeds a predefined threshold, derived from the underlying empirical data. *Evaluations* include financial, environmental, psychological, and co-adoption factors. *Aggregation* follows a logit model. *Exogenous processes* include technological learning and the policy context. The model simulates diffusion under different policies such as financial incentives and energy efficiency standards.

4.4 Discussion of the mappings

The SEED model, alignment with the metamodel is particularly strong. SEED includes a wide range of agent attributes (e.g. socio-economic factors, preferences, stock variables) and a multi-criteria choice module with event-based triggers. Its environment captures key metamodel components such as technologies, cost evolution, and social networks, while transformers account for filtered and distorted information exchanges. SEED goes further by incorporating multiple agent types (e.g., households, services, industry) and by explicitly linking behavioral outcomes to energy system feedback via STEM. This demonstrates the metamodel's flexibility to represent complex, multi-sectoral agent systems.

The BedDeM model aligns well with the metamodel reference architecture, with minor deviations due to implementation choices or domain-specific needs. The trigger is a separate component, not part of the choice module, reflecting an implementation difference. BedDeM lacks Physical assets and Rules of interaction components, and its transformers lack distortion, which were not needed for the specific domain or research question.

The Co-adoption model aligns well with the metamodel, particularly through its detailed agent attributes, rule-based triggers, and use of logit models for utility aggregation. Although knowledge assets and distortion mechanisms are not explicitly included, they could be integrated. Grounded in empirical data, the model complements the metamodel by illustrating how data-driven parameterization can enhance the framework.

Across all three cases, minor deviations are not signs of misalignment but rather reflect intentional simplifications or domain-specific adaptations. The consistent mapping of core concepts such as attributes, decision-making structure, environment, and communication demonstrates that the metamodel provides a robust concept for interdisciplinary dialogue. It enables model comparison without constraining methodological diversity, supporting both theoretical abstraction and practical implementation.

5 Conclusion

Understanding individual decision-making in the energy transition requires interdisciplinary research and integrated modeling approaches. In this paper, we propose a metamodel designed to facilitate interdisciplinary dialogue in the design of ABMs. By mapping several existing models to the metamodel, we show that it can effectively capture and represent core concepts across models. The metamodel serves as a communication tool, offering a structured approach to representing social science and humanities perspectives in energy modeling, establishing a common language, and helping identify data needs for parameterizing behavioral mechanisms. As a flexible reference architecture, the metamodel supports shared understanding while accommodating diverse methodologies—laying the groundwork for systematic, multidisciplinary comparisons of agent-based models. Looking ahead, the metamodel can support model design, teaching, interdisciplinary collaboration, and greater transparency in behavioral assumptions. It enables integration with techno-economic models such as STEM [24], enhancing long-term energy planning through behavioral insights.

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