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Agent decision-making: The Elephant in the Room - Enabling the justification of decision model fit in social-ecological models

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ABSTRACT

Agent-based models are particularly suitable to reflect the dynamics of humans, nature, and their interactions, making them a crucial approach for understanding social-ecological systems. The formalisations of human decision-making are central to resulting model behaviours. Despite awareness of the complexity of human behaviour in social-ecological systems research, scholars tend to represent human decision-makers as simplified, perfectly informed rational optimisers, without explicitly considering the fit with decision context. Key reasons are a lacking uptake of social theories and insights. To advance, we need a practice of reflecting, sharing, and inquiring on the justification of the decision model fit with its context. This paper stimulates this practice by 1) supporting the justification of decision model (DM) fit by describing the DM landscape and providing guiding questions; and 2) by supporting researchers in considering alternative DMs through a survey-based impression of modeller practices, and through highlighting DM frontiers as inspiration for future research.

1. Introduction

The Anthropocene made us humans more conscious than ever of our role in current environmental crises. This awareness is reflected in an increasing recognition that research needs to account for complexity, context-dependency, and dynamism underlying human behaviour in social-ecological systems (SES) (Fulton et al., 2011; Schill et al., 2019; Weber and Johnson, 2009) to develop models for understanding, predicting, and/or managing anthropogenic problems (Geels, 2010; O'Brien, 2018). SES reflects an integrated perspective of humans-in-nature (Berkes and Folke, 1998; Folke et al., 2016) regarded as complex adaptive systems (CAS). CAS assumes a diversity of system elements that continuously interact. From these interactions patterns emerge, which in turn shape these elements and their interactions (Holland, 1995; Levin, 1998). Simulation models play an important role in understanding the role of humans in such complex systems (Weber et al., 2019). Agent-based models (ABMs), in particular, pioneer in encompassing the diversity of human behaviour and social interactions while connecting the diverse locations and social institutions in which human entities and collectives operate. However, SES simulation scholars have yet to fully explore and benefit from the body of knowledge in the social and behavioural sciences (Constantino et al., 2021; Wijermans et al., 2020).

While engaging with and contributing to the social and behavioural sciences is at the heart of (agent-based) social simulation (see e.g., the Journal of Artificial Societies and Social Simulation, the leading journal

Abbreviations: ABM, Agent-based model; DM, Decision Model; SES, Social-ecological systems (including: social-environmental systems, socio-environmental systems).

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in Social Simulation), its scientific contributions are still rarely centred around anthropogenic problems. Many real-life SES challenges involve (cross-scale) interactions, a plethora of influence factors, and feedback loops in systems with constantly altering decision contexts (Ungar, 2021). These complex and changing realities in which individuals, collectives, and institutions decide and (inter)act, create a diverse set of situations reflecting different facets of human decision-making. How to represent human decision-making, and any resulting behaviour are thus key consideration when designing, evaluating, and using SES models that embrace the challenge of addressing the role of humans and their behaviour in environmental crises. However, a central question arises: how do modellers actually decide which human decision-making model to use for underpinning the resulting SES dynamics?

Despite a general awareness of the complexity of human behaviour in SES research, there exists a tendency to represent human decision-makers as simplified, perfectly informed, rational optimisers, without explicitly detailing how well such a representation fits with the decision and its behavioural context. Reviews of ABMs and their decision models (DMs) have rather clearly stressed the importance of and the need for representing more social realism in ABMs, and pointed out how prevalent fully rational/economic approaches remain, e.g., (Brown et al., 2017; Groeneveld et al., 2017). However, an increasing number of models is embracing this potential of ABMs to reflect and engage with complexity, and implement other, non-rational decision factors, processes from theory and/or empirical findings, (e.g. Dressler et al., 2018; Lindkvist et al., 2017; Narasimhan et al., 2017; Robertson and Choi, 2012; Sanga et al., 2021; Scholz et al., 2014; Taghikhah et al., 2021; Wijermans et al., 2020) and shows in the often-used ODD+D protocol for ABM documentation that strongly advocates the detailing of the DM dimension (Müller et al., 2013).

To learn from and build forth on each other's work, several reviews describe current practices in formalising DMs that are currently in use, e.g. (An, 2011; Kennedy, 2012; Rounsevell et al., 2011). Notably, some reviews point out which approaches or aspects are relevant to improve behavioural realism *in general* (Brown et al., 2017; Groeneveld et al., 2017; Kennedy, 2012) or within a specific domain, e.g. (Castro et al., 2020) in ABMs of energy transition, (Huber et al., 2018) in ABMs of EU agriculture, or (Klabunde and Willekens, 2016) in ABMs of migration.

Reviews generally underline that resolving the lack of realism requires an increased uptake of relevant theories and insights from different scientific domains, especially across the usual natural science and social science divide. The present lack thereof unsurprisingly often culminates in a misfit between the implemented decision models (DMs) and the SES phenomena a model aims to reflect. In particular, the social, cognitive, and behavioural sciences offer alternative theories and empirical evidence that explain human behaviour in various contexts (Constantino et al., 2021).

Though we agree that an under-utilisation of relevant theories and insights is an important issue, we would like to advance this discussion toward more careful considerations of DM-context fit as a core practice towards more realistic representation and thus model behaviour. One might feel tempted to address the current realism problem by simply including *some* socialness (e.g., social influence via social network interactions), and/or by adding *some* boundedness in agent reasoning (e.g., a utility satisficer or some knowledge limitations) and, voilà, we have more behavioural realism.

However, to advance research practice, we need to take the reflection on DM choices to another level. Our paper thus seeks to support this desirable improvement in modelling practice. When modelling, we always simplify a target phenomenon, and an improved modelling practice includes a reflection on the target social reality and what it entails for agents' decision context. We thus see a clear need for deeper discussion about which DM formalisation fits a decision context to better align with the model's target/phenomenon of interest. For some specific decision modelling situation, a self-interested, maximising, rational actor may be justified. However, supportive reasoning is rarely present in publications, presentations, or peer-review interrogations. The decisions of individual agents and their micro level assumptions are crucial for studying the emergent meso/macro-dynamics of interest in an ABM, as these dynamics arise from individual agents' decisions and interactions. To increase the suitability, transparency, and reproducibility of their findings, SES modellers should thus embrace it as part of their practice to reflect on their assumptions regarding the decision-making mechanisms underlying human behaviour in the context under study. With such reflective practice better embedded in the modelling endeavour, we may then be able to advance our understanding of situated decision-making and more meaningfully engage in theory development.

But how do we move from extant assumptions on DM fit to explicitly expressed considerations? We suggest SES modellers would benefit from (1) *developing a critical and reflective practice to justify DM fit* with model target (decision context) by navigating the landscape of different DMs, i.e. use descriptive dimensions in which DMs can reside to be able to select, position, and challenge DMs; and (2) *to consider alternative DM options* beyond the default micro foundations by tapping, for instance, into theories and empirical evidence from the social sciences that are often not considered; or exploring remaining frontiers in DM development. The goal of this paper is thus to support justifying DM fit by a) describing the decision model landscape in which we highlight different dimensions that have been suggested for making sense of DMs, and b) providing guiding questions to scrutinise DM-context fit (section 2). We subsequently support researchers in considering alternative DMs by providing a survey-based impression of DM selection practices of agent-based social simulation modellers, and by pointing out important frontiers as inspiration for future research (section 3).

2. Justify your decision model fit

With the rise of ABMs[1] and the growing attention paid to the role of humans in SES, existing ABMs cover a vast range of SES contexts in which human decision-making takes place. For being able to navigate and make sense of the DM landscape, organising principles such as taxonomies or frameworks appear crucial. SES research is (in)famous for its usage of frameworks (for a comparison see (Binder et al., 2013)) as they have inspired scholars to connect, communicate, and collaborate, e.g., SES framework (Ostrom, 2009). Using a common framework or theory enables finding, using, engaging, and/or generalising relevant insights, and helps identify relevant under-explored areas of research. Yet, little guidance is available for SES modellers on how to select and decide among DMs. Notable exceptions are e.g. (Constantino et al., 2021; Schlüter et al., 2017). Within the social simulation community, several attempts have been made to provide overarching principles for categorising DMs. These provide useful dimensions for SES modellers to navigate and implement DMs relevant for their decision context. Below, we overview the DM landscape by providing relevant dimensions and highlighting suitable frameworks/taxonomies of DMs, that one could adopted to change the practice of ABM and social simulation communities in modelling human behaviour.

2.1. Dimensions of decision models (taxonomies/organising principles)

There are several reviews that seek to support transparency and thus access to ABMs (Dilaver and Gilbert, 2023) and specifically aim at capturing current DM practices, e.g. (An, 2011; Kennedy, 2012; Rounsevell et al., 2011). They stress the importance of heterogeneity, social, non-rational, emotional, or subconscious nature of human behaviour in general (Brown et al., 2017; Groeneveld et al., 2017; Kennedy, 2012) while others point at domain-specific needs to improve behavioural realism (e.g. Castro et al., 2020; Huber et al., 2018; Klabunde and

[1] This herein includes Individual-based Modelling (IBMs).

Willekens, 2016). However, to enable modellers to systematically reflect on the fit of a DM with a target phenomenon, we herein present especially useful frameworks/taxonomies that can help SES modellers to navigate the DM landscape across disciplinary and/or field boundaries. Each of these papers offers its unique way of organising DMs that may be relevant for our readers to make sense, situate, and target models of human decision-making relevant for their own ABM decision context, or when reading or reviewing the work of others. We briefly summarise and reflect on each of these frameworks/taxonomies, including their strengths and weaknesses, and their unique contributions for application.

Methods note. The articles covered below were selected based on the author team's collective experience with using certain sources for selecting, positioning, and challenging own DMs. We cross-referenced our selection with the resources indicated by other social simulation modellers. We also restricted our selection to contributions that take a meta-position into which models can be positioned or that enable reflection on aspects relevant for one's own decision context. We thus excluded categorisations that are mainly based on functional form (e.g., utility function models) or scientific discipline (e.g., mathematical, or psychological models) as these do not support us in meaningfully arguing for or against a specific DM fit. We by no means claim to be exhaustive herein, of course, but very much hope to stimulate a discussion, also in terms of suggestions regarding additional sources of support at this level.

2.1.1. Agent decision architecture dimensions

Balke and Gilbert (2014) suggest six dimensions to systematically compare different agent decision architectures, see Table 1. They provide guidance in choosing a DM, given certain levels of simplicity vs. complexity needed for answering a specific research question. The review covers 14 agent decision architectures, targeting diversity (not completeness) and focusing on whole architectures, not specific aspects, e.g., learning.

Strengths. This review is comprehensive. The dimensions for comparing agents' DMs encompass a diversity of important aspects a model might include (cognitive, social, affective, normative, and learning). It is complemented by a discussion of situations in which the architectures are relevant to include.

Weaknesses. The review could be overwhelming for a (SES) reader. The grouping of dimensions is based on communities of practice, leaning towards the cognitive sciences. This can make it difficult to link to the social simulation or SES communities. In contrast to the other frameworks (below), this framework does not enable an easy categorisation or positioning of a given social simulation model or behavioural theory. Moreover, it does not clarify why e.g., norms and learning receive more attention than other concepts. Guidance for a reader on how to apply these dimensions to designing formal models of human behaviour is not included either.

Table 1
Dimensions for comparison of agent decision architectures (adapted from Table 1, p2 (Balke and Gilbert, 2014)).

Dimensions	Explanation
Cognitive	What kind of cognitive level does the agent architecture allow for: reactive agents, deliberative agents, simple cognitive agents or psychologically or neurologically inspired agents?
Affective	What degree of representing emotions (if any at all) is possible in the different architectures?
Social	Do the agent architectures allow for agents capable of distinguishing social network relations (and status), what levels of communication can be represented and to what degree can one use the architectures to represent complex social concepts such as the theory of mind or we-intentionality.
Norm Consideration	To what degree do the architectures allow to model agents which can explicitly reason about formal and social norms as well as the emergence and spread of the latter?
Learning	What kind of agent learning is supported by the agent architectures?

2.1.2. Varieties of Rational Choice Microfoundations

In their introductory book chapter, (Wittek et al., 2013) lay out the diversity of behavioural micro foundations assumptions in models of rational choice given three dimensions of DM assumptions: rationality, preferences, and individualism. The rational choice approach reflects a family of theories that explain social phenomena as outcomes of individual action. The type of rationality and preference assumptions that relate to the canonical assumptions on cognitive abilities are relaxed progressively, like e.g., the dimensions of the Model Social Agent (see next subsection). The varieties of individualism relate to the degree to which (only) the individual level and its micro-level mechanisms or social-structural aspects are required to explain a social phenomenon. These dimensions then form an organising principle for different (assumptions underlying) models of rational choice (Table 2) (see Table 3).

Strengths. The dimensions support the categorisation of models, acknowledging the diversity of ways in which rationality assumptions can be relaxed. For example, automatic (non-deliberate) responses based on past experiences - procedural rationality - are still a form of rational choice; or that selfishness is not by necessity a component of rational choice models; and social relations and culture can be a part of (weaker) rational decision-making as part of the (structural) individualism. This enables a more nuanced manner of critiquing models as criticism currently often targets the canonical hyper-rational model of agent rationality. Most importantly, however, these micro foundations overview stimulates and provides a language for being explicit about these core assumptions.

Weaknesses. The dimensions themselves are restricted to rational choice models. Just like in the Model Social Agent (herein below), these DMs may not align with the (understandings/workings of a) decision-making context. Moreover, although being well-written, the number of definitions, sub-dimensions, and parts of the continuum possibly not applicable to rational choice can render the Rational Choice Microfoundations less accessible, leading to a requirement for deeper engagement and learning on part of the modeller.

2.1.3. Model Social Agent

"The Nature of the Social Agent" (Carley and Newell, 1994) highlights the need to bring more behavioural realism into ABMs. In the authors' view, empirical reality puts demands on a model along two dimensions: with more realism, there is a gradual increase in needed **knowledge** and in the limitations of **processing** capabilities of an agent (Fig. 1), culminating in the idealised "Model Social Agent" when the situation is most enriched with attuned (but limited) capabilities.

Strengths. The dimensions and the resulting matrix are intuitive as it follows a familiar gradient: omnipotent, rational, bounded rational, etc. The matrix is a powerful tool to position models and theories, bringing analytical clarity and terminology to represent DMs in SES models. It thereby helps to communicate what a model's limits are, i.e., what tasks are out of scope and the gradients provide a useful perspective on 'how far' one can potentially go in representing human decision-making, given the specific research context of interest, also for future work.

Weaknesses. A potential downside of this approach is that it has not been widely adopted in research which affects its pragmatic use in communication with peers. Explaining the two dimensions and its combinations each time is not always afforded in conferences and volume restrictions in papers. The Modal Social Agent also overlooks concrete pointers regarding ways to formalise these different DMs.

2.1.4. The Contextual Action Framework for Computational Agents

The Contextual Action Framework for Computational Agents (CAFCA) (Elsenbroich and Verhagen, 2016) aims at supporting the modelling of agent decision-making where agent decision-making is context dependent. It serves as an organising principle for categorising

Table 2
Varieties of Rational Choice Microfoundations (adapted from Table 0.1, p6 ((Wittek et al., 2013)).

Assumption	Thin/strong rationality <-->Thick/weak rationality			
1. Rationality	Full rationality	Bounded rationality	Procedural rationality	Social rationality
2. Preferences - *Selfishness*	Opportunism	Egoism	Linked-utility	Solidarity
2. Preferences - *Materialism*	Tangible resources	Intangible resources	Physical wellbeing	Social wellbeing
3. Individualism	Natural	Social	Institutional	Structural

Table 3
Frameworks and their use.

Framework/taxonomy	Core dimensions/features	Use {selecting, positioning, challenging}
1. Agent decision architectures	Cognitive, affective, social, norms, learning	Selecting
2. Varieties of Rational Choice Microfoundations	Rationality, Preferences, Individualism	Selecting, Positioning, challenging
3. Model Social Agent	Knowledge, Processing	Positioning, challenging
4. CAFCA	Reasoning, Sociality	Positioning, challenging
5. MoHuB/HuB-CC	Characteristics (situational, stable), processes (perception, behaviour)	Selecting

existing social simulation models, social ontology, and social and behavioural science theories. Depending on how an agent considers others in its decision-making and the type of reasoning used, this results in nine agent decision-making modes (Fig. 2).

Strengths. CAFCA is powerful for reflecting on own and others' DMs and it is simpler (3x3 + level of concreteness) than e.g., the Model Social Agent. It supports model design by conceptualising the target system and enables modelling sociality that allow for creating relatively simple agents since complexity is reflected in the context rather than in the agent. Lastly, CAFCA enables thinking beyond the default ways of DM thought and stimulates the consideration of alternative decision modes. These dimensions are inclusive of non-rational and non-individualistic ways of conceptualising human decision-making, such as agents with a collective-driven decision-making mode.

Weaknesses. Due to its focus on existing modelling work, CAFCA also inherits limitations of extant models, lacking aspects such as emotions, for instance. It also leaves questions regarding the role that e.g., the physical environment might play, and whether the reasoning dimensions can capture important SES decision contexts.

2.1.5. MoHuB and HuB-CC frameworks

MoHuB (Schlüter et al., 2017) and its psychology-grounded extension HuB-CC (Constantino et al., 2021) are frameworks aiming to support the broader use of social theories by ABM modellers (MoHuB) and SES researchers (HuB-CC). They serve as tools and provide a common language to describe, identify, compare, and communicate about theories underpinning agentic decision-making. The frameworks thus provide concepts that are useful for describing or explaining human behaviour (e.g., perception, behaviour, situational and stable characteristics etc.), but they are themselves not a model or theory, i.e., they postulate no causal relationships between the elements, nor do they claim that all elements need to be present at the same time (see Fig. 3).

Strengths. These frameworks were made for an SES audience as they have been developed with social *and* natural environments in mind while engaging with DMs. Equally powerful is the grounding of the frameworks' elements and processes in social and cognitive science insights, which simultaneously form a useful set of considerations regarding what aspects are relevant to include in a DM given a specific decision-making context. Although they are frameworks and thus not an integrated theory or model, they provide some guidance for the identification of elements and processes, and connection to relevant theories that enable finding a suitable DM.

Weakness. These frameworks do not provide a means of positioning own or others' decision models in the DM landscape, unlike Varieties of Rational Choice Microfoundations, the Model Social Agent, or CAFCA. Despite considering the social and the natural environment, the frameworks can still be rather focused on individualistic decision-making and may prove to not provide enough guidance for those interested in modelling collective and/or organisational decision-making.

2.2. Use of frameworks and their dimensions

The reader might be frustrated to read about the many options of what to consider rather than guidelines for dealing with these choices. However, we chose against making framework to reflect or embed them all. All these frameworks have their own value, and some may work more intuitively than others to reflect on own or others' work. However, we do have some recommendations for use:

Selecting - Identifying the DM needs for a model you are building. Use the above frameworks to identify important dimensions for your model-context fit and search the extant literature for suitable DMs based on dimensions identified as important. Agent decision architectures, and MoHuB/HuB-CC are the most purposive for asking important DM selection questions and provide both language and theoretical anchor points for delving into the DM literature based on categories derived from the frameworks.

Positioning - Stating what kind of model you have developed within the landscape of DMs also allows for contrasting own work vs. that of

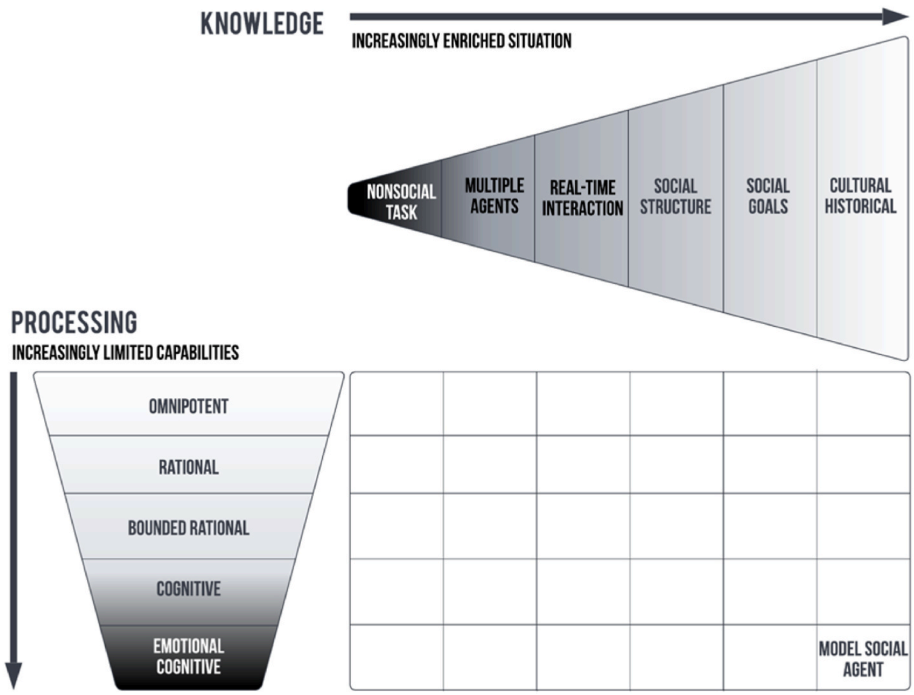

Fig. 1. Dimensions of the model social agent (Carley and Newell, 1994).

		SOCIAL DIMENSION		
		INDIVIDUAL	SOCIAL	COLLECTIVE
REASONING DIMENSION	HABITUAL	Repetition	Imitation	Joining-in
	STRATEGIC	Rational choice	Game theory	Team reasoning
	NORMATIVE	(institutional) rules	(social) norms	(moral) values

Fig. 2. The Contextual Action Framework For Computational Agents (CAFCA; Adapted from Fig. 1, p135 in (Elsenbroich and Verhagen, 2016)).

others which enables a scientific dialogue about modelling choices, practices, and descriptions. CAFCA, Varieties of Rationality and Model Social Agent allow for clear communication of what your DM is able and not able to do.

Challenging - Questioning or critiquing the foundational assumptions and/or model implementation choices made by other modellers. This is particularly important when working as a peer/friendly reviewer tasked with assessing the contribution of a model (paper). While essentially all frameworks above provide input and arguments for reflection, especially Varieties of Rational Choice Microfoundations, the Model Social Agent, and CAFCA provide suitable dimensions for such a task.

Note that apart from the different ways one can utilise these frameworks, each framework stresses certain DM dimensions that their creators consider important. Thus, they have their own blind spots and may on their own not readily apply to any decision context humans encounter. For example, they may not adopt a SES perspective without extensions or combination with other conceptual frameworks and thus lack the explicit acknowledgement of dimensions that allow placing agent decision-making of humans (and other animals) in their biophysical environmental context and dynamics. Another realisation is that these frameworks have often been developed based on insights from (western) social and cognitive sciences, and may thus not be suitable for reflecting DMs of agents in other, non-Western decision-making contexts, see e.g. (Bates, 2007; Leaf, 2008).

2.3. *Towards a practice of justifying DM fit*

Though most modellers would indicate *that* they inform their choice for a decision model, it often remains invisible in publications, conference discussions, or peer-review questioning *how exactly* this decision came about and *what* the considerations were. We envision such a consideration and explication of why a particular DM is considered a good (context) fit to become a standard community practice, forming part of the discussion during peer-review processes, or even leading to a norm of performing sensitivity analyses with or comparing competing alternative DMs that have been considered. It would then be fruitful to take stock and map DMs in use as well as converge criteria used to consider DMs (un)fit across DM context. It should have become clear by now that we strongly encourage researchers to share and inquire regarding DM choices presented in models. We aim for such practices and debates, alongside and possibly even in interaction with documentation standards, to enable long overdue advances in our field through enhancing the scientific debate.

We realise this is a challenging task and our section 2.1 undoubtedly added more complexity to the task. To provide some guidance for navigating this space, we created a set of guiding questions that can be asked concerning the decision context to derive a list of requirements for a DM (see Table 4), as well as questions that enable a critical reflection of a DM given the decision context it operates within (see Fig. 4). Both table and figure hold similar content, but they allow for a slightly different engagement. Table 4 provides the overview and details of how

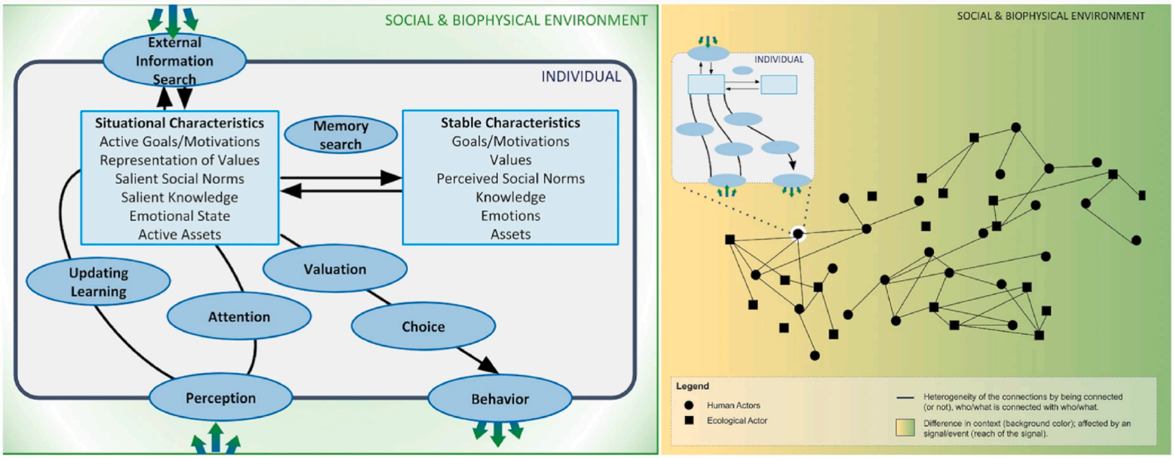

Fig. 3. HuB-CC framework (adaptation from MoHuB) (Constantino et al., 2021).

Table 4
Questions about the decision context towards a set of Decision Model (DM) requirements.

	Question
Type of decision-making	Is decision-making deliberate and/or subconscious?
Time	Do the past or present (experiences) and/or the future (expectations) play a role? What is the decision's time horizon?
Locus of influence	Does the decision take own and/or others' outcomes into account?
Sociality influence	Do (social) norms, culture, or other social aspects play a role on the decision of the agent?
Limitations	Are any known/identifiable/explicit biases at play? What is the role of agents' capacity/resources on agents' ability to decide? Spatial implications on actions?
Decision context	Are there any uncertainties involved? E.g., risk of a hazard? Social or ecological uncertainties?
Decision itself	Is a decision made one time (irreversibly) or do agents decide repeatedly (corrections possible)?
Meta	Do you agree with the theoretical assumptions behind a model?
Agent learning	Is the agent's perception of the environment static or is it updated through the decision and/or across model runs? And do DM rules remain constant or is the DM adaptive? Is an agent's ability to perceive their environment affected by their decisions and model responses?

questions regarding DMs may look like. Fig. 4, on the other hand, highlights the core questions to ask from the perspective of your agent's DM, and some keywords for sub-questions that follow, but also stimulate complementing with relevant questions beyond what we generated herein.

Method note. To arrive at both table and figure, we authors met several times in the form of online workshops. These enabled a sequence of discussions on i) what we read in review papers, ii) the dimensions from the articles in section 2.2., and iii) the learnings from the surveyed practices of the social simulation community members. Together with the design of the survey and a concluding discussion about the relevance of certain questions, we developed the subsequent table and figure. Note that this collection of questions is a product of our collective experience with the literature and practical DM sensitivities from different scientific domains. There is some overlap with existing work, such as questions asked in the ODD+D protocol (Müller et al., 2013), at the same time these serve as an invitation to ask other relevant questions. Key in the proposed practice: Exercise these reflections during your design stage, as well as during the communication stage while modelling, but also as a reviewer or discussant of models during conferences, peer-reviews etc.

3. Consider alternative decision models

Modelling decision-making is challenging, particularly if going beyond the default approach in one's particular field. We regard the diversity of modellers as a rich source of inspiration, not only to avoid reinventing the wheel, but also as a good base to start from. A plethora of different theories are ready for use, see e.g. (Constantino et al., 2021) for an overview.

We encourage modellers to continue using such resources and offer some additional inspiration through 1) an overview of common practices of our peers, including their wishes regarding decision-making aspects in simulation models, which we obtained via our survey among social simulation modellers, and 2) by exploring the frontiers in modelling decision-making, where we specifically highlight a set of frontiers that the author team discussed in-depth and provide some examples for each, as inspiration for future work.

Methods note. To gain insights into existing practices of DM modelling, we conducted a survey among social simulation modellers in July 2021. Our questionnaire received 117 responses from the community we addressed via an active mailing list for those involved in computer simulation in the social sciences (SIMSOC@JISCMAIL.AC.UK) and via snowball-sampling in our personal networks. The survey focused on the practices of modelling agent decision-making, the resources used, and on identifying present needs and barriers (see the Appendix for more details). The frontiers were developed in several online workshops of the authors in which we discussed which frontiers to include and their content, silent-writing and giving feedback sessions, the text was finalised by a subgroup of 1–3 authors.

Concerning the survey questions specifically, to provide a common (=comparable and detailed) way for modellers to express details about their DM practices and wishes, we decided to separate the decision-making representation (e.g., utility function or IF-THEN rules) from the aspects included into the decision-making. Overall, this is not a trivial task, and we once again realised how difficult it was to find a common language that would be interpreted in the same way by different modellers when specifying their DM characteristics. Guided by the insights from the dimensions (section 2.1), we specified different aspects that could be selected. It was important for us to stress aspects and processes that characterise the (internal) state of an agent (motivations, memory, expectations, values) and its structural limitations (knowledge and processing limits), but also what influences the agent is exposed to (social and/or biophysical environment, what it perceives and how, social situatedness in culture, social norms), but also how an agent may change (different types of learning, situational modes of decision-making).

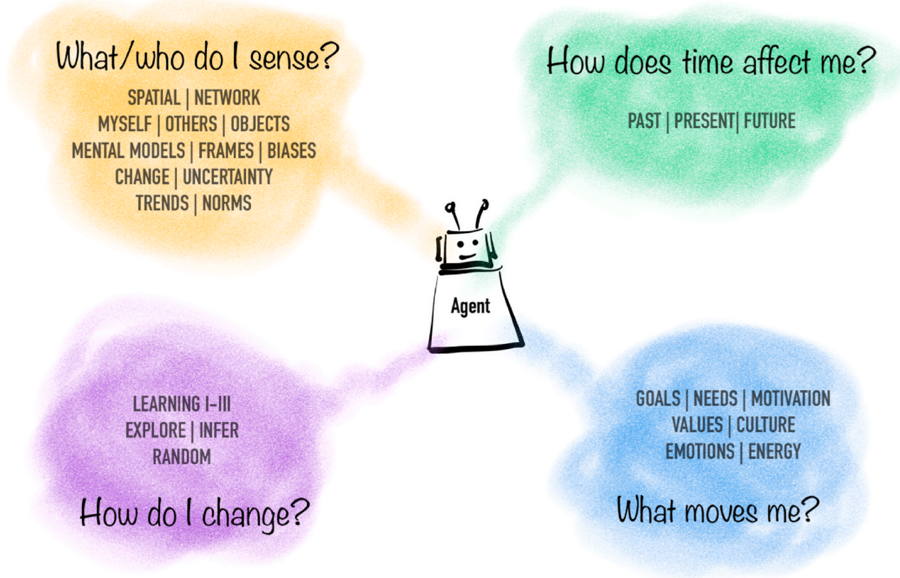

Fig. 4. Questions about the DM model for an agent to scrutinise fit with a DM decision context.

3.1. What do others do, or wish, regarding DMs?

To consider DM alternatives we decided to investigate DM practices and wishes of our social simulation peers' via a survey. Fig. 5 shows the answers to these two questions. Before interpreting these numbers, note that the overwhelming majority (87%) of agent-based social simulation modellers responding to our survey model an agent as an individual, i.e., the decision-making of one single entity, e.g., a human. For others, an agent would reflect a group of individuals (28%) or an organisation (15%).

Concerning current practices, >70% DMs of survey respondents reflect goal-oriented decision-making, influence from past experience (memory) and other agents on agent behaviour, with agents that change their internal state as their variable values change (learning-I). Least included (≤21%) are agents that can infer new rules (learning-III) or involve emotions and culture in their decision-making. Analysing future wishes reveals relevant aspects/processes that scholars wish to use but are not presently using. These are learning (II and III) and emotions, directly followed by culture and values.

3.2. Explore research frontiers

3.2.1. Who decides? DMs to represent individuals, groups, or organisations

3.2.1.1. The challenge. Most DMs represents single individuals, however, the decision-making processes of a group or an organisation may differ considerably from individual decision-making, e.g., multi-loop learning, organisational change. Many relevant social-ecological systems involve a diversity of individuals, groups, and organisations. The field could benefit from expanding this predominant focus on representing individuals in DMs to groups and/or organisations since, societally speaking, these social aggregates can be important agents in terms of the social-ecological contexts modelled. Such approaches, however, come with two modelling challenges. First *to what extent, and in what specific context are DMs of individuals inherently different from aggregate entities, such as collectives, businesses, or governmental entities?* To know whether the distinction is important in a specific context, and how, matters greatly in terms of allowing for model reuse or re-application and for avoiding unnecessary complexity. Specifically, if DMs include theories that are developed for individuals, how applicable/valid are those for groups or organisations? Instead of using theories tailored to individuals at social aggregate levels, different theories may be more applicable and provide opportunities to conceptualise, formalise, implement, and test other theories, and, not least for building bridges between theories operating on different levels (e.g., Lindkvist et al., 2017; Lorscheid and Meyer, 2021; Orach et al., 2020; Secchi and Cowley, 2021; Stöppler, 2021). Second, *groups and organisations are made up of individuals; both the individual and collective levels may be studied simultaneously.* Explicitly formulating decision-making at both the individual level (contributing to collective-level strategies) as well as at the collective level is relevant for understanding many SES models, e.g. giving autonomy to consumer groups through energy cooperatives (Fouladvand et al., 2022), and may help to connect different disciplines studying the same phenomenon.

We note, however, that in non-western contexts, using western social and cognitive theories to describe decision-making in non-western cultures and contexts can be misleading. Indeed, individual Indigenous (i.e., cultural) heuristics are well formed for decision-making, but are based instead on the recognition that individuals exist in *culturally* constituted organisations (Leaf, 2008) and steeped in Indigenous *holism* (Berkes and Berkes, 2009). Fieldwork might therefore be necessary to choose the appropriate representative DM - for instance fuzzy cognitive mapping, e.g.'s, (Dubos et al., 2023; Rooney et al., 2023), combined with scenario building (Klenk and Meehan, 2015) have each shown promise in non-western SES modelling, that can furthermore be interwoven with ABMs (Giabbanelli et al., 2017). However, in some cultures, prediction, planning, and forecasting are considered anathema to Indigenous philosophies (Bates, 2007) and we therefore advocate for cultural sensitivity to be adopted by western researchers, and other ways of knowing to be recognised, valued, and respected.

Example(s). Fouladvand et al. (2022) created a model representing agents at different levels of aggregation in the formation of thermal energy communities, in which households organise to share the development of local heating technology. Their model simulates individual agents that can take part in the community, the community board (representatives for the aggregate entity), and the municipality that may subsidise developments in the respective community. The representative board is explicitly modelled: how the community is supported by individual agents, as well as how the board makes decisions about the community (e.g., investing in shared wind power). Consequently, the local energy community emerges out of the interaction between agents that represent households and at the higher community board level.

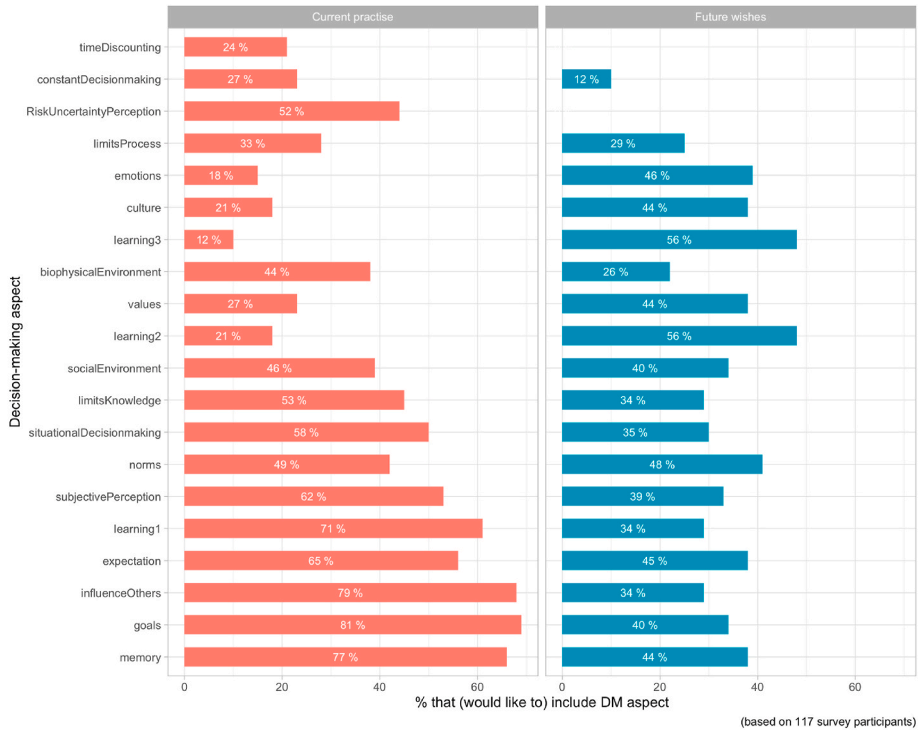

Fig. 5. Overview of decision-making aspects modellers presently include (left) and wish to include in future (right)[12].

Haer et al. (2020) present an ABM that integrates the dynamic behaviour of governments and residents into a large-scale flood risk assessment framework. Government agents are representatives for households in larger regions and decide on flood protection measures. In smaller regions, household agents (representing all households in a small region) decide on climate adaptation efforts for their buildings. Both types of decisions are economic in nature, explicitly considering climate-related and other uncertainties. The model studies the effects of different strategies for governments (reactive or proactive) in combination with decisions of residents.

3.2.2. When decide how? Context-sensitive DMs

3.2.2.1. The challenge. Most models are designed specifically for the context to which they are applied. This often means an agent is dealing with a particular task in a particular setting. However, it often remains unclear what or to what extent elements, choices, and results are specific to that target phenomenon of the model. This is important information if one is considering reuse of a model, but also opportunity for working with DMs applicable to a broader context to reflect agents able to operate in more complex environments. This translates to the need to specify the 'context-space' for which a model is relevant or valid, or to formulate specific requirements regarding context.

Context is a container term consisting of all things around the agent that it is made aware of and/or sensitive to (Edmonds, 2012). It can represent at least three concepts. First, context can refer to the specific case study/application, e.g., representing a specific time/geographical region. Second, context may refer to the specifics of the problem that is modelled (which factors are of interest, what time frame is relevant, what actors are involved). Third, context may refer to the 'environment' which captures external drivers that some others would call 'the scenario' e.g. (Duinen et al., 2015). In some cases, the latter includes the direct physical environment, e.g., in terms of natural resources that are input to the modelled system, or it may include the social environment, e.g., norms, narratives, or collective emotions.

Since models are typically developed to be used in a particular context, this could lead to limited generalisability and hamper advancement by which new modelling results and system insights are obtained. Making the context-space explicit would give opportunities for systematic comparison of models and modelling outcomes and allow for greater reuse of models. If models had an explicitly described context-space, it would also enable others to find all the relevant models for a studied phenomenon in a specific context. Such a process may enrich how we study phenomena with a plurality of relevant models. For this frontier, we may take inspiration from ecological modelling, where it is rather common to specify the context-space and build on existing (more generic) models (Grimm, 1999).

We see four steps in tackling this context challenge. First, to develop protocols to communicate about the specific context for which a model was developed and when it becomes relevant or valid. This includes a specification of how the term 'context' is interpreted in terms of the three context concepts mentioned above. Second, to develop guidelines on how to validate models against the respective context-space, and for how this should be performed within a peer-review process which is focused more on the merits of an individual scientific paper rather than the underlying model and/or modelling advancements. Third, to develop approaches that facilitate using the concept of context-spaces, e.g., taking inspiration from exploratory modelling and analysis, or adopting machine learning approaches for finding patterns that represent phenomena in a wider modelled context. A final step is to work on how generic/flexible models operating in a broad(er) context(s) can be acknowledged and appreciated by academic and broader societal audiences.

Examples. A model with a broad and flexible context is Consumat (Jager et al., 2000; Jager and Janssen, 2012) and its more recent successor HUMAT ((Jager et al.., In Press). Consumat, contains different modes of behaviour that agents may select depending on the specific context, i.e., the level of uncertainty (low, high) and the level of need satisfaction (low, high). Decision modes include repetition (repeating earlier actions), imitation (repeating others' actions), inquiring (learning about possible behaviours), and optimising (deliberate what behaviour leads to a desired outcome). Agents can switch between different modes and a population of agents can differ amongst their individual behavioural modes, which is a powerful feature in Consumat's ability to represent a diverse range of emergent patterns.

3.2.3. Learn and decide, decide and learn? DMs that can adapt and change

3.2.3.1. The challenge. In many ABMs, agents need to be able to change to be able to adapt, respond or anticipate what occurs in their social and/or biophysical surroundings. Learning can lead to changes in ideas, information, knowledge, routines, norms, opinions, institutions, ways of deciding, including both learning new aspects as well as un-learning old ones. Learning is deeply connected to changing behaviour and is a key part of understanding SES and their dynamics (Pahl-Wostl, 2009). The concept of learning comes with many definitions, it can occur at different levels (Abdulkareem et al., 2020), and can manifest in different types, at different times, see Fig. 6. Considering learning for ones DM thus involves considerations operates on the intersection of learning type, social scale, and timing.

Learning Type I-II-III: reflect the different depths of learning, inspired by the notion of single-, double-, and triple-loop learning from organisational learning and natural resource management (e.g., (Crossan et al., 1999; Pahl-Wostl et al., 2007; Tosey et al., 2012) but adapted to ABMs: *Learning-I*: updating values in variables; *Learning-II*: changing decision rules; and *Learning-III*: adding/inferring new decision rules. SES ABMs rarely include Learning types II and III. However, when aiming to study e.g. regime shifts and sustainability transitions (e.g., Filatova et al., 2016) agents are placed in contexts that may require them to change their ways of engaging with(in) their changing context (Learning III). The core challenge lies in designing agents to respond to these situations and to revise and adapt their decision-making rules. In current ABM learning-I is dominant (87%), many (approx. 50%) modellers indicate have to wish for give their agents learning II and III abilities (see Fig. 5). To enable the integration of learning II and III, genetic algorithms are a well-known and mature technique e.g., (Manson, 2006)).

Social Scale: relates to the first frontier – who decides – and focuses on which entity or social aggregate learns, e.g., learning as an *individual* (individual level), *group* or *organisation* (group level), or even whole *communities* or *societies* (societal level), e.g., (Abdulkareem et al., 2020). Several scholars point out the importance of discussing the social scale and learning at these levels in SES, see e.g., (Crossan et al., 1999; Newig et al., 2010; Pahl-Wostl et al., 2007). Most modellers (60% in our survey) integrate some form of individual learning in their models where agents learn at the micro level through experiential/direct learning, or via communication. However, collective, social, or organisational learning, i.e., learning at the meso level or macro level, poses a proper challenge to model and they are applied much less frequently. Learning at the collective and societal levels might be Learning-I, –II, or –III (e.g., organisational double-loop learning). Moreover, learning can reflect changes within the individuals explicitly within a social group (that changes itself too) - or, if the group is modelled as a single agent, within that one agent. Such learning is often (partly) also individual learning explicitly in a social setting, from this micro-level learning collective learning emerges, these outcomes on the social aggregate level again affect individual learning (immergence) etc. This is relevant for societal learning, e.g., when studying a norm shift, emergence of new social movements). To represent group or societal learning are challenges inherent on how to represent social collectives in models, including the selection and integration of relevant theories given the social aggregation level and context. The Social Identity Approach (Scholz et al., 2023) is one way of integrating and conceptualising groups and organisational

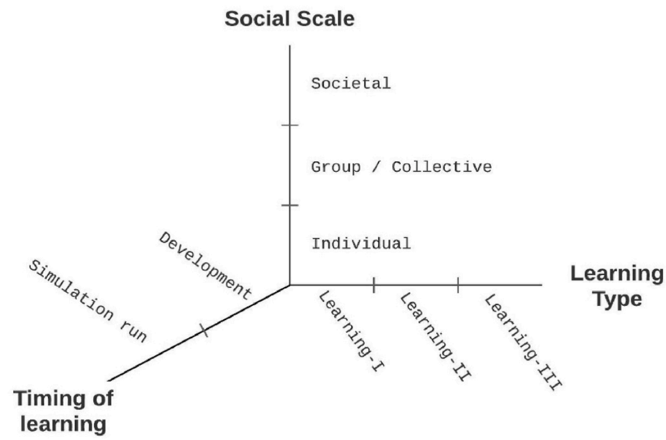

Fig. 6. Different scales and levels at which learning in DMs can occur (adapted from (Scholz, 2016)).

research offers several ways to conceptualise and model organisational learning (Tosey et al., 2012).

Timing of learning: relates to when learning takes place in the model, i.e. during model development or during model runs. Models that learn during development are for example models that use data and machine learning – e.g., deep neural networks. DMs then remain constant while in operation or are dynamically updated if agents are able to learn further during model runs. The models and learning we discussed thus far reflect learning during simulation runs. The different times of learning can occur at all social scale levels and may include any and all learning types. Related to timing, such approaches may allow agents to learn from past experiences, and optimise future behaviour as well as DMs including probabilistic programming and reinforcement learning, e.g. (Hung and Yang, 2021; Lee et al., 2017).

Example(s). A model with learning II is presented by (Koning and Filatova, 2020). They simulate how increasing probabilities of environmental hazard experienced by households could lead to the Bayesian updating of individual worry, hence triggering agents to switch from a subjective and rather rational assessment of expected outcomes to a total risk avoidance strategy, with both decision heuristics validated by empirical survey data. A group learning model is presented by (Scholz et al., 2014) where changes in factual and social (role-related) knowledge at the individual level is influenced by the social context and in turn creates social artefacts (consensus).

3.2.4. Automating decisions? DMs created by algorithms

3.2.4.1. The challenge. Besides the theoretical, heuristic, and participatory underpinnings for the algorithms used by agents to make decisions, machine learning can also be used to inform rule sets and behaviours (Manson, 2005; 2006; Ravaioli et al., 2023). This usually requires sufficient empirical data that associates the social and/or environmental context and personal attributes (demographics and values) with agent behaviours within an DM. When training a machine learning algorithm that agents will use, a key challenge lies in having sufficiently *high-quality* and granular data to represent an adequate diversity of agents across both space and time, as well as across relevant drivers of behaviour. We emphasise ‘high-quality’ because while the advent of ‘big data’ analytics suggests that there will be no problem with algorithms handling the data volume to cover all different combinations of contextual and agent attributes a simulation might need, big data may only have short-term validity, or not even be true at all (veracity/verifiability), or require significant pre-processing to extract information of value due to the variety of formats and content in big data, see, e.g. (Gutta, 2020).

A second issue with some machine learning algorithms is

[2] Note that in the results of Fig. 5 two values are missing for future DM wishes: (‘time discounting’ and ‘risk perception’); these were by mistake not selectable options in that part of the survey.

explainability. Neural networks are popular machine learning algorithms, especially since the advent of deep learning, and have a much greater issues with explainability than alternative methods with semantic structures, such as decision trees or Bayesian belief networks. Neural networks are useful for deriving an algorithm with a known fit to the data and when it is not particularly relevant how that answer is reached. Zhang et al. (2023) provide a comprehensive review of machine learning and ABM use cases, pointing out that, especially in the case of neural networks, more research is needed if the learned behaviour is required to be explainable.

In the absence of large volumes of high-quality, micro-scale data, machine learning methods can still be used to derive algorithms for agents that reproduce macro-scale data (or patterns) as an emergent phenomenon. Inverse generative social science (IGSS; (Epstein, 1999; 2023; Vu et al., 2019) is one way to achieve this goal. IGSS is conceived as an automated method for Generative Social Science (Epstein, 2012), in which plausible explanations for social phenomena are 'grown' from the bottom-up. IGSS uses evolutionary programming methods to build simple decision-tree and equation-based algorithms for the agents over repeated generations of simulation runs, until algorithms and parameters are found that reproduce the desired emergent behaviour. Structured as equations and decision-trees, the algorithms lack memory and iteration, and so do not have full computational power (as per Turing Machine equivalence), but they are interpretable by humans. Besides significant CPU time requirements for effectively evolving a simulation that reproduces a phenomenon of interest, another issue is that there may be diverse means by which the phenomenon can be generated. However, if a researcher with access to a big enough computer simply needs at least *one* means of generating it rather than necessarily *the* means, then IGSS is a viable option.

3.2.4.2. Example(s). Heppenstall et al. (2008) linked a genetic algorithm (GA) to an agent-based model for the purpose of optimising decisions of individual retail outlets in setting gasoline prices. At first, large scale data sets were mined to identify the decision-making of competing firms over space and time, and this knowledge assisted the GA in optimising retailers' future strategy. (Manson, 2005) embedded genetic programming (GP) into an ABM for exploring future scenarios of land use. Here, GP was used to evolve a set of rules/decisions for the agents to implement. Sánchez-Maroño et al. (2015, 2017) developed an agent-based model of everyday pro-environmental behaviour decision-making using discretization, clustering, feature, and decision-tree learning algorithms.

4. Conclusions

Whether your endeavour lies in choosing an adequate decision model for the target phenomenon of your model, positioning your existing model in the landscape of models in the extant literature, or if you are reviewing a submitted paper regarding either of those questions, we are hoping to inspire thought and debate. We imagine conferences with in-depth discussions concerning the fit of an agent's Decision Model (DM) with the decision context it is targeting to operate in; journal reviewers routinely requesting considerations of DM-context fit; and a reflective practice in which modellers consider, find, and reflect upon alternative DM options for the models they are developing and detail their choice reasoning in their publications. This is highly relevant not least to improve the quality of models, and realism they are able to approximate, but also to build our capacity to advance our insights on situated decision-making and meaningfully engage in theory development.

In this paper, we aim to support such a practice to enhance model quality in ways that we are currently often missing. Particularly during these Anthropocene times when the role of human behaviour is increasingly acknowledged, both with regard to its impact on, e.g., the environment, and with regard to its behavioural diversity, we suggest discussions of DM models and their intended context-fit should see a strong increase in quality and intensity. Models are often called upon to reflect more behavioural realism since this is central to gain relevant model outcomes. To enable a practice of modellers reflecting on DMs and considering alternatives provides insights into the dimensions of the DM landscape - models that otherwise tend to perish in the dark. Justifying DM choices both during the selection/design process and in communicating about our work, enable positioning models in the literature, as well as raise meta-questions regarding the DM's target decision situation fit.

Our plea for a better match between the DM and the decision context does *not* equate to modellers having to prove their DM to be 'the best'. An agreement on the best model is meaningless when working in an interdisciplinary or transdisciplinary setting: various perspectives on the same problem can be meaningful and embracing such diversity holds much value. We do, however, see vital importance in making the choice for particular DMs explicit, as well as arguing why and how the DM fits with the model's decision context, not least to detect DMs unfit for the target decision context. Communication about these choices is the only way to grow a common understanding and develop best practices. This is similar to the process of writing this paper: we had to take the time and effort to find a common language and become an interdisciplinary team.

We support this challenge by providing the above overview of dimensions used in social agents' frameworks, helping to assess and position one's own selected DMs and the DMs in the literature we are confronted with. We additionally included some inspiration for enabling the community to consider alternatives when modelling and we provided some insight into current DM practices in the community, and we identified key areas where wishes currently deviate from practice. Furthermore, we highlighted a set of frontiers to inspire future work towards including, comparing, and contrasting alternative DM options, leading to overviews of the DMs landscape and converging the selection criteria of context fit.

In short, we hope to have encouraged you - in any role in which you might engage with models of human behaviour - to question the DMs strongly and potentially loudly you come across regarding their decision model to context fit. We thereby hope to instil a sense of urgency and improved practice of explicitly sharing DM considerations and choices, and thus increase the usefulness of our models which we so dearly need for dealing with our anthropogenic challenges.

Software availability

N.A.

Declaration of competing interest

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

Data availability

The survey data has been included as supplementary file. The description of the survey questions and results are provided in the Appendix

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.envsoft.2023.105850.

Appendices.

To gain insights into the practices of modelling human decision-making and behaviour, we conducted a survey in July 2021 among social simulation modellers. We received 117 responses from the community we reached via an active mailing list for those involved in computer simulation in the social sciences (SIMSOC@JISCMAIL.AC.UK) and via snowball-sampling in our personal networks. The survey focused on the practises of modelling agent decision-making, the resources used, and on identifying present needs and barriers. The survey was executed using google forms.

In this paper we made use of the question 2, 8 and 10 from the survey we set up broader as we were interested to learn about it, however while writing this paper, for our story only these 3 questions were considered relevant. We provide the data as supplementary information in an XLS file: SurveyData-DecisInABM.xls, with a tab for each question with data cleaned up so one can analyse it.

Survey questions used in section 3.1 | the practice of modelling

For this we contrasted question 8 and 10:

Table A1
Overview survey questions about current practice (left) and wishes (right) in decision making representation

Question 8 - current practise	Question 10 - wishes for future
Indicate what your decision-making representation typically involves (Please indicate all that apply): o Motivation(s)/goal(s:) o Memory (past experiences) o Expectations (about the future) o Subjective perception (what is seen/experienced is interpreted differently from one agent to the other) o Perceptions about risky and uncertain outcomes (subjective probability of hazard events; lack of knowledge about exact distributions of probabilistic outcomes) o Emotions o Values o Social Norms o Culture o Social environment o Influences other agents o Biophysical environment o Knowledge Limits (e.g., imperfect information) o Processing limits (e.g., time, selections restrictions) o Learning-I (update values in variables) o Learning-II (changing rules) o Learning-III (adding/inferring new rules) o Situational decision-making (depending on the situation the decision-making rules/logic changes) o Constant decision-making: Always the same decision-making, independent of situation o Time discounting (i.e. consider future outcomes less valuable than current) o Other: …	What would you be interested in including in the future in your agent's decision-making? (Please indicate all that apply) o Motivation(s)/goal(s:) o Memory (past experiences) o Expectations (about the future) o Subjective perception (what is seen/experienced is interpreted differently from one agent to the other) o Emotions o Values o Social Norms o Culture o Social environment o Influences other agents o Biophysical environment o Knowledge Limits (e.g. imperfect information) o Processing limits (e.g. time, selections restrictions) o Learning-I (update values in variables) o Learning-II (changing rules) o Learning-III (adding/inferring new rules) o Situational decision-making (depending on the situation the decision-making rules/logic changes) o Constant decision-making: Always the same decision-making, independent of situation o Other: …

Note that 2 items were inadvertently missing from question 10, not repeating all aspects one wishes to include. This concerned: Perception about risky and uncertain outcomes AND Time discounting (see blue text).

Table A2
Frequency and percentage of DM representation practise and wishes.

DM representation	Current use		Future use wish	
	Freq	%	Freq	%
goals	81	69%	40	34%
memory	77	66%	44	38%
expectation	65	56%	45	38%
subjectivePerception	62	53%	39	33%
RiskUncertaintyPerception	52	44%	0	0%
emotions	18	15%	46	39%
values	27	23%	44	38%
norms	49	42%	48	41%
culture	21	18%	44	38%
socialEnvironment	46	39%	40	34%
influenceOthers	79	68%	34	29%
biophysicalEnvironment	44	38%	26	22%
limitsKnowledge	53	45%	34	29%
limitsProcess	33	28%	29	25%
learning1	71	61%	34	29%
learning2	21	18%	56	48%
learning3	12	10%	56	48%
situationalDecisionmaking	58	50%	35	30%
constantDecisionmaking	27	23%	12	10%
timeDiscounting	24	21%	0	0%

Survey questions used in section 3.2.1 | Who decides frontier

For this we used the answers to question 2 of the survey: What do the agents you usually model represent (you can select more than one):

o Agent = one individual (reflecting the decision making of one single e.g., human, fish, tree, etc.)
o Agent = group of individuals (reflecting the aggregated decisions of e.g., a household (regardless of the #members), a forest, a fleet, etc.)
o Agent = organisation (reflecting the decisions of an organisation e.g., company, farmer association, interest group, regulatory institutions, insurance etc)
o Other: please specify

Table A3
Overview number of modellers in survey that model agent as individual, group or institution or a combination of these.

Agent =	Frequency	Percentage
individual	102	87%
group	33	28%
organisation	18	15%

Note participants of the survey could indicate more than one option. Of the 117 participants 30 indicated multiple ways they represent agents.

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