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Agent-Based Modelling of food systems: A scoping review on incorporation of behavioural insights

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ABSTRACT

Agent-Based Models (ABMs) offer a flexible and interdisciplinary approach to food system modelling by simulating the interactions of heterogeneous agents within social and environmental contexts. Given their bottom-up structure, the validity of ABMs critically depends on the behavioural assumptions underpinning agent decision-making. This scoping review examines how behavioural assumptions are informed in ABMs applied to food systems by analysing 55 relevant studies. We classify approaches into two categories: data-driven methods and behavioural theory. Our findings reveal that more than a third of the included studies rely on neither behavioural theory nor behavioural data to inform their behavioural assumptions in the model, raising concerns about model validity. The highlighted gaps in the usage of behavioural data and theory to inform ABMs, emphasizes the need for a stronger focus on robust behavioural assumptions in ABMs of food systems.

Contents

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1. Introduction

Food systems encompassing production, distribution, and consumption, linked to environmental and social factors are becoming increasingly complex (Peters and Thilmany, 2022). They are shaped by politics and regulation, technological innovation, changes in the economic and social landscape, and climate change stressors, all of which influence transitions towards more sustainable (or unsustainable) practices. Given these high complexities, modelling and simulating food systems to understand transitions, policy impacts, and economic consequences remains challenging (Alonso-Adame et al., 2024). While models inevitably represent simplifications of the real world, advancements in computational power enable the incorporation of more details.

Agent-based models (ABMs) are an approach that simulates interactions between heterogeneous agents and their environments, making it a promising method for capturing the complexity of food systems. The agents in the model can represent e.g. individuals, firms, farms, or governments, all of them engaging in dynamic interactions that shape their decisions. In ABMs, agents are allowed to make decisions based on their unique behavioural characteristics. Moreover, agents are embedded within environments that encompass social, economic, and environmental factors, all of which influence their decision-making processes. The high flexibility and non-linear structure of ABMs, which can be tailored to specific modelling needs, make them particularly valuable for incorporating interdisciplinary knowledge (Castelli et al., 2024). Considering that multiple disciplines are needed to understand food systems, ABMs have been proposed as a suitable tool for simulating and understanding these systems (Alonso-Adame et al., 2024).

With a particular focus on individual agents' decision-making, ABMs are considered a bottom-up approach. This implies that understanding overarching phenomena is based on an understanding of individual decisions. Therefore, it is crucial to have a robust understanding of individual decision-making, or at least a strong rationale for the assumed behaviour within the model. Given that behavioural assumptions are a core principle of ABMs and model outcomes can be highly sensitive to these assumptions (Brown et al., 2021; Wens et al., 2020), this scoping review aims to investigate how publications justify the behavioural assumptions they impose in ABMs of food systems. Furthermore, we aim to gain a general understanding of ABM applications in food system modelling, including model resolution, covering different food system focuses, spatial extent, and agent aggregation, as well as the use of modelling protocols to support transparency.

Recent literature reviews covered food system related fields. For example Teeuwen et al. (2022) examine modelling approaches to food security. They specifically investigate the available methods, such as ABMs, equilibrium models, and econometric models, and analyse their applications across different contexts. Their findings demonstrate that ABMs are frequently employed in food security modelling, particularly focusing on production aspects. Castelli et al. (2024) published a review on four specific modelling approaches: ABMs, computable general equilibrium models, integrated assessment models, and dynamic stochastic general equilibrium models, examining their applications within the water, energy, food, and ecosystem nexus. Regarding ABMs, Castelli et al. (2024) highlight the lack of a common framework starting from the underlying assumptions to individual decision making and mathematical optimization. Additionally they mention the inherent complexity of ABMs as a potential barrier for their wider application. With a similar focus on food, energy, and water nexus, Magliocca (2020) shows in his systematic review that a third of the selected papers do not support their behavioural assumptions in ABMs with behavioural theory.

Another publication closely related to our work is the systematic review of ABMs used to model sustainability transitions by Alonso-Adame et al. (2024). Their results suggest that ABMs demonstrate particularly strong outcomes when integrated with other methods, such as GIS, system dynamics, or Bayesian approaches. While their focus lies in evaluating the overall suitability of ABMs for agri-food system modelling, we extend this work by offering a more detailed investigation into model specifications when applying ABMs. Specifically, we examine how behavioural assumptions are informed within ABMs applied to food systems. Lastly, Groeneveld et al. (2017) conducted a review on the theoretical foundations of human decision-making in ABMs, focusing on land use models. They find that many decision-making submodels in ABMs lack a strong theoretical basis. Our work is closely related in its focus on behavioural assumptions but shifts the topical emphasis to food systems and, given that their data only includes publications until 2013, also provides a more recent perspective. In addition, we broaden the scope by considering not only behavioural theory but also behavioural data as a basis for informing behavioural assumptions.

This scoping review builds on and complements these prior studies by offering a deeper understanding of how behavioural assumptions are justified in ABMs for food system modelling. Specifically, we distinguish between two primary sources for informing behavioural assumptions: behavioural theory and behavioural data. Our findings reveal that a significant proportion of the reviewed publications (≈36%) do not base their behavioural assumptions on either behavioural data or theory, raising concerns about model validity. Regarding spatial extent, ABMs are frequently applied to smaller areas, such as city or municipality levels, often with a focus on production. Furthermore, most reviewed publications are situated within the field of environmental economics. Finally, we observe limited adherence to common modelling protocols in the application of ABMs to food systems.

The paper is structured as follows. In Section 2, we introduce a food system framework to categorize the publications. Section 3 shows underlying behavioural assumptions in ABMs and decision-making processes. It furthermore introduces behavioural theory and data that can inform ABMs. In Section 4 the scoping review is presented. It includes the variables collected in the reviewing process, the search methodology, and a presentation of the results. Section 5 discusses and concludes the scoping review.

2. Food systems

Food systems are receiving increasing attention in politics, with numerous reports for policy advice highlighting their importance. These reports often focus on issues such as providing nutrition for a growing population, or promoting and providing healthy diets (World Health Organization, 2022; Townsend et al., 2016; United Nations, 2015c). Another focus is on improving resilience against climate change and advancements in sustainable food production (Swinnen et al., 2022; FAO, 2023; United Nations, 2015a,b). As the political relevance of food systems increases, they have also become a more prominent area of study in the academic field.

The direction of academic research on food systems is closely aligned with the political narratives mentioned above. According to Béné et al. (2023), key issues in the academic discussion on food systems include their capacity to meet the nutritional demands of a growing global population and the challenge of ensuring that healthy diets are accessible to all. In addition to these health-focused issues, there is a growing body of literature on the social and environmental dimensions of food systems, such as promoting equitable benefits, addressing inequalities, and mitigating the environmental impact of food production (Béné et al., 2023). In this scoping review, we are specifically interested in the stream of literature that explores the sustainability of food systems, analysing how they can be transformed to meet the ecological, societal, and economic demands of current and future generations.

Given these different orientations to studying food systems, multiple research domains aim to explain and model food systems from distinct

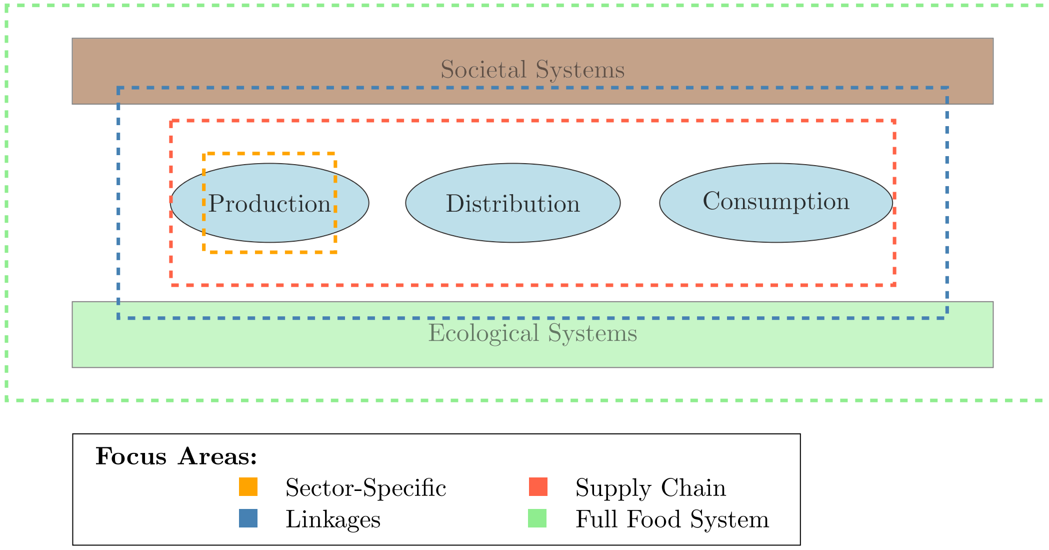

Fig. 1. Focus areas in studying food systems (Peters and Thilmany, 2022).

perspectives. Three primary fields can be identified (Teeuwen et al., 2022): First, the economic domain, which focuses on aspects such as taxation, incentives, and trade, in relation to sustainability goals, for instance through taxes on emissions, incentives for adopting climate friendly practices, or policies encouraging less deforestation. Second, the bio-physical domain, which examines factors like crop growth, hydrology, and environmental processes, and is central to understanding the ecological limits of food production and the environmental impacts of agricultural practices. Third, the social domain, which emphasizes the human component of food systems, including cultural, behavioural, and social influences that shape sustainable consumption, equity in access to resources, and community resilience. In this review, we will primarily focus on the economic and social domains.

Another important aspect of food system models is the spatial extent. Food systems can be analysed at areas, ranging from villages and municipalities to countries and entire continents, each providing unique insights (Teeuwen et al., 2022). At smaller extent, it is possible to examine the specific behaviours of individual producers and consumers, while at larger extent, broader assumptions must be made to account for the actions of many individuals within the system. These overarching assumptions can significantly influence the results, so it is crucial to be mindful of the underlying complexity, especially when modelling food systems at a larger spatial extent.

Lastly, another dimension in the examination of food systems involves the specific focus within the system, as illustrated in Fig. 1. At the centre are the core components of the supply chain: production[1], distribution, and consumption. Food system analysis can be sector-specific by examining only one component, such as production, distribution, or consumption, respectively. Alternatively, it may adopt a broader supply chain perspective, encompassing all three components. Food system modelling can further expand this perspective that is defined as linkages by Peters and Thilmany (2022). This approach integrates the supply chain with elements beyond production, distribution, and consumption. The broader perspective can include interactions with societal and ecological systems. When focusing on linkages, the analysis connects only some of these broader elements. In contrast, a full food system focus looks into all previously mentioned aspects, providing a comprehensive view of the food system including the supply chain linked to the societal and ecological system (see Fig. 1) (Peters and Thilmany, 2022).

When reviewing food systems literature we have to acknowledge the high number of dimensions that can differ between studies. First, studies may cover different **topic domains** of food systems e.g. health-focused (enough and healthy nutrition) or environment-focused (climate change adaptation and sustainability). Second, they can differ by their **research domain** (economic and social). Third, studies may be conducted at different **spatial extents**: village/city, municipality, country, continent, and global. Fourth, the **food system focus** may differ, ranging from sector specific, supply chain, linkages, to full food system. These constitute key variables in our literature review (see Section 4.1), where we consider all four dimensions to capture the diversity of ABM applications in food system research.

3. Agent-based modelling

At the core of ABMs are agents which are autonomous entities with specific attributes that interact with each other and their environment based on individual goals. While definitions vary across the literature (Macal and North, 2005; Bonabeau, 2002; Mellouli et al., 2004), common characteristics include heterogeneity, autonomy, goal-directed behaviour, interaction, and often adaptation or learning capabilities.

By simulating the interactions of heterogeneous agents, ABMs enable researchers to explore system behaviour and potential future scenarios. Their flexibility in incorporating diverse decision-making behaviours and multidisciplinary knowledge makes ABMs particularly well-suited for modelling complex systems such as food systems (Alonso-Adame et al., 2024; Macal and North, 2005; Bonabeau, 2002).

3.1. Behavioural assumptions

3.1.1. Behavioural theories

ABMs are grounded in the understanding of individual behaviour. Consequently, ABMs follow a bottom-up approach, aiming to explain system-level occurrences by modelling individual decision-making processes (Robinson et al., 2007). The validity and reliability of these individual decision processes are crucial and should, therefore, be based on either behavioural theory, behavioural data, or ideally, both.

Overall, the majority of behavioural assumptions in ABMs are grounded in economic theories (Steinbacher et al., 2021; Groeneveld et al., 2017). In most economic theory, there are three core assumptions which define a rational agent. First, preferences are consistent and well-defined. Second, the chosen option aligns best with these preferences.

[1] Some models include processors as an intermediate stage between production and distribution. Here, we consider processors as part of production.

Third, all relevant information is considered in the decision-making process (Von Neumann and Morgenstern, 1947). Following that, one can also define bounded rationality. Here, it is assumed that one or more of these assumptions are violated due to factors like limited information, restricted cognitive abilities, and time constraints (Müller et al., 2013). A key behavioural model using bounded rationality is the *Satisficing* model developed by Simon (1956), which describes a sequential decision-making process in which agents assess options one by one and stop as soon as a satisfactory option is found.

Rationality and bounded rationality are considered behavioural paradigms and can be used independently to explain decision-making processes in ABMs. Both paradigms are frequently employed to inform ABMs (Groeneveld et al., 2017). However, these paradigms often serve as foundational concepts for behavioural theory, which provide a more sophisticated theoretical basis for explaining decision-making processes in ABMs.

Behavioural theories used to inform ABMs vary widely and originate from diverse fields, including economics, sociology, and psychology. One commonly applied theory is Expected Utility Theory (EUT), which assumes that individuals primarily seek to maximize profit or utility (Von Neumann and Morgenstern, 1947; Groeneveld et al., 2017). This theory is grounded in the assumption of rational behaviour. Another theory based on rational choice is the Theory of Planned Behaviour (TPB), introduced by Ajzen (1991), which focuses on behaviour-specific motivational factors that influence intention and, consequently, behaviour. Another major theoretical framework used in ABMs is game theory, which can incorporate both rationality and bounded rationality. Game theory provides a formalized approach to strategic decision-making and is widely applied in modelling interactions between agents.

Finding a suitable theory can be challenging given the vast number of available options. However, certain tools can facilitate the search and improve comparability when selecting a theory for human behaviour and decision-making. Schlüter et al. (2017) developed the MoHuB (Modelling Human Behaviour) framework, which helps identify and apply an appropriate theory to a given model. This framework addresses challenges such as the fragmentation of theories and knowledge across disciplines or conflicting theoretical implications. Additionally, it broadens the scope of potential theories, allowing for the combination of multiple approaches to better suit the specific needs of ABMs.

3.1.2. Behavioural data

Regarding data, there are various types that can capture behavioural information to inform ABMs. We focus on three main types of data collection methods for ABMs adapted from Robinson et al. (2007). First, sample surveys can be used to gather quantitative data, often covering larger geographical areas. While this method is effective for collecting substantial amounts of data, its quality heavily depends on the survey's design and implementation (Robinson et al., 2007, p. 33–35). Second, observational data involves collecting data in the field which is often qualitative and helps developing theories rather than proving them. This approach can provide valuable insights into how social systems function organically, while reducing biases from the research setups (Robinson et al., 2007, p. 36–37). Third, experiments, conducted in either field or laboratory settings, utilize gamification techniques to reveal behaviour. For example, participants may be assigned artificial roles and asked to react to specific scenarios. This method is particularly useful for studying targeted behaviours under controlled conditions (Robinson et al., 2007, p. 39–40).

Additionally, machine learning approaches, particularly those involving reinforcement learning algorithms, can complement traditional methods (Zhang et al., 2021). By leveraging historically observed data, these models replicate learning processes and allow for the introduction of alternative decision strategies that may not have been previously observed. While machine learning methods depend on data, they are often well suited to extract additional insights and introduce flexibility in modelling behaviour in ABMs.

3.2. Domains of influence

Another aspect in ABMs is the interaction between agents and their environment (Wilensky, 2015; Müller et al., 2013). These interactions shape agent behaviour, as agents are influenced by complex interrelationships across various domains, including economic, social, and environmental spheres. Within the social and environmental domains, interactions can be divided into two main pillars: impact and influence. In the social domain, *impact* refers to how an agent's decisions affect others, while *influence* involves how decisions are shaped by social groups, such as through peer pressure. In the environmental domain, *impact* relates to how an agent's actions affect the environment, often involving altruistic considerations that may reduce utility. *Influence* in this domain includes positive or negative effects from nature, like recreational benefits or weather effects on harvest. The economic domain, however, lacks this distinction between impact and influence, focusing solely on the costs and benefits of the respective individual (Groeneveld et al., 2017).

Other influential factors can affect decision-making and may be incorporated into ABMs. For instance, the temporal and spatial aspect, such as agents' past experiences in the specific area, can shape expectations for future decisions. This is closely linked to agents' ability to learn, such as through knowledge sharing (Müller et al., 2013). Adaptation is another important factor, though it differs from learning as adaptation is a more passive form of adjustment that requires less cognitive effort (Dibble, 2006; Groeneveld et al., 2017). Lastly, uncertainty about future developments can also influence decision-making, particularly through risk aversion (Müller et al., 2013). There are many additional factors that can influence decision-making. However, for this scoping review, we limit our focus to the factors described above, adapted from Groeneveld et al. (2017) and Müller et al. (2013).

A crucial aspect of developing ABMs and their respective domains of influence on the decision-making process, is the clear communication of the model structure to facilitate a better understanding, comparisons with other studies, and ensure reproducibility. In this context, the most commonly used protocol for ABMs is the Overview, Design concepts, and Details (ODD) protocol, initially developed by Grimm et al. (2010), first published in 2006 and updated in 2010. A valuable extension, ODD + D (ODD + Decision), was introduced by Müller et al. (2013) to incorporate a focus on the decision-making process within ABMs. The ODD + D protocol is particularly relevant as it explicitly captures domains of influence on the agents. Given that ABMs rely heavily on decision-making processes, the additional emphasis on decisions in the ODD + D protocol helps ensure higher standards in model development compared to the ODD.

3.3. Modelling approaches

The modelling approach in ABMs is often aligned to the behavioural assumptions and decision-making process in the model. At its core, three main approaches are commonly used: optimization, heuristic, and stochastic methods (Groeneveld et al., 2017).

For **optimization-based approaches**, agents are often assumed to behave rationally. Drawing from EUT, agents are commonly modelled with an objective function aimed at maximizing their utility. This approach includes constraints that represent the complexity of influential factors and the interactions between agents as well as between agents and their environment. Optimization in ABMs can be implemented using programming solvers that facilitate this structured search for a optimal solution.

Heuristic methods are more aligned with bounded rationality, where agents do not seek the best possible solution but rather aim for a satisfactory one (Réveillac, 2015). This closely relates to the *Satisficing* model by Simon (1956), which is often used to provide a theoretical understanding for bounded rationality. Heuristic methods are commonly implemented in ABMs through simulation procedures or decision algorithms such as decision trees, allowing agents to follow simpler, rule-based strategies.

Finally, **stochastic approaches** model decision-making as a probabilistic process, where agents make choices based on likelihoods rather than fixed rules or optimization criteria. This is particularly useful in contexts of uncertainty, where randomness plays a role in shaping outcomes. Stochastic elements can help reflect the unpredictability of real-world behaviour and enrich models by introducing variability (Groeneveld et al., 2017).

Notably, ABMs often integrate multiple decision-making approaches within a single model. For example, stochastic components can be layered onto heuristic or optimization-based frameworks to introduce flexibility and enhance realism. Likewise, heuristics can guide optimization strategies, or different methods can be applied at different decision levels, allowing for more nuanced and adaptable agent behaviour in complex systems.

4. Applications of ABMs in food system modelling

This scoping review examines the application of ABMs in food systems research, with a particular focus on how behavioural assumptions are integrated. Given the interdisciplinary nature of food systems and the flexibility of ABMs in representing heterogeneous agents, understanding how behavioural factors are incorporated is crucial for model validity and applicability. Therefore, our first research question is:

How are behavioural assumptions justified in agent-based models of food systems, and to what extent do these models incorporate data-driven insights or behavioural theory to inform agent decision-making?

Given that the choice of resolution in ABMs can also affect behavioural assumptions and complicatedness[2] of a model, we are furthermore interested in:

What spatial extent, food system focus, and levels of agent aggregation are applied in agent-based models of food systems?

4.1. Extracted variables

Building on the concepts of food systems and ABMs introduced in the previous sections, we compiled the variables to be extracted from the reviewed literature (Table 1). These variables include metadata components such as author, journal, publication type, and year. Additionally, we included variables relating to the food system, as explained in Section 2. Specifically, we collected information on the topic domain, the research domain, as well as the spatial extent and focus, to enable an analysis of the resolution.

Furthermore, we gather data on the ABMs applied in the included publications. The structure for this data collection is guided by Section 3. We extract information about the agent type, the behavioural paradigm, and the underlying theory as well as whether the model incorporates behavioural data. Moreover, we document details about influence domains and individual decision-making. We also assess whether a protocol for model specifications is provided, whether the model has been validated, and which modelling approach has been used.

4.2. Search methodology

The scoping review began by selecting databases based on two key criteria: the availability of necessary metadata (e.g., title, abstract, keywords) and the reproducibility of the data collection. Databases like Google Scholar, AgEcon, FAO, World Bank, and JSTOR are excluded due to issues such as insufficient metadata, non-reproducible search algorithms, or data extraction difficulties. Instead, the review relies on Scopus and Web of Science, which provide comprehensive metadata in easily extractable and reproducible formats. These databases align with prior systematic reviews in the field (Achter et al., 2024; Groeneveld et al., 2017; Kremmydas et al., 2018; Teeuwen et al., 2022).

Table 1
Overview of extracted variables and data types used in the scoping review.

Category	Variable	Coding/Values
Publication meta-data	Author	[*str*] Authors names
	Journal	[*str*] Journal name
	Year	[*int*] Publication year
	Document type	[*str*] Article, Conference Paper, Book, Note
Food system	Topic domain	[*str*] Health, Environment, other
	Research domain	[*str*] Economic, Social, other
	Spatial extent	[*str*] Village/City, Municipality, Country, Continent, Global
	Focus	[*str*] Sector-specific (production, distribution, consumption), Supply chain, Linkages, Full food system
Agent-based modelling	Agents	[*str*] Individuals, Households, Firms/Farms, Sector, others
	Behavioural paradigm	[*str*] Rationality, Bounded rationality, other
	Behaviour theory	[*str*] Expected Utility Theory, Multi-attribute Utility Theory, Theory of Planned Behaviour, Theory of Reasoned Action, Game Theory, other, none
	Behavioural data	[*str*] Survey, Observational, Experiment, Machine Learning
	Influence domains	[*str*] Economic, Social (impact/influence), Environmental (impact/influence)
	Decision-making	[*str*] Spatial, Time, Learning, Adaptation, Uncertainty
Methodology	Protocol	[*str*] ODD, ODD + D, others, none
	Modelling approach	[*str*] Optimization, Heuristic, Stochastic
	Model validation	[*str*] Yes, No

Developing an effective search term, or query, is essential for scoping and systematic reviews as well as meta-analyses. The query is evaluated on two dimensions: its ability to identify all relevant papers (*recall*) and to do so without retrieving excessive irrelevant work (*precision*) (Grames et al., 2019). To optimize these, researchers use prior knowledge and insights from similar reviews. Based on this approach, tailored queries for Web of Science and Scopus have been developed. These queries target papers that focus on food systems and the use of ABMs. For Scopus, we used the following search term:

```
TITLE-ABS-KEY (food W/4 *system* AND ("agent-based model*" OR abm))
```

This query searches the title, abstract, and keywords of papers where the term "food" appears within four words of "system" and includes mentions of "agent-based model" or "ABM".[3] The word "system" is flexible, allowing for prefixes or suffixes, so it matches any word containing "system". For "agent-based model", the query accommodates any characters following "model", covering variations such as "modeling" or "modelling". The hyphen between "agent" and "based" does not affect the search results, so the query yields the same hits with or without it. For Web of Science, the query is adjusted to its syntax:

```
TS=(food NEAR/4 *system* AND ("agent-based model*" OR abm))
```

The scoping review focuses on applications of ABMs in food system modelling. The inclusion criterion is that publications must present an

[2] We use the term *complicatedness* as defined by Sun et al. (2016). Hence, complicatedness refers to the model structure such as number of agents, variables, and interactions.

[3] We acknowledge that this is a very precise search term e.g. excluding "individual-based model"; "multi-agent model"; "agent-based simulation". However, we assume that for the purpose of a scoping review our sample is sufficiently large to identify research gaps allowing a high precision query.

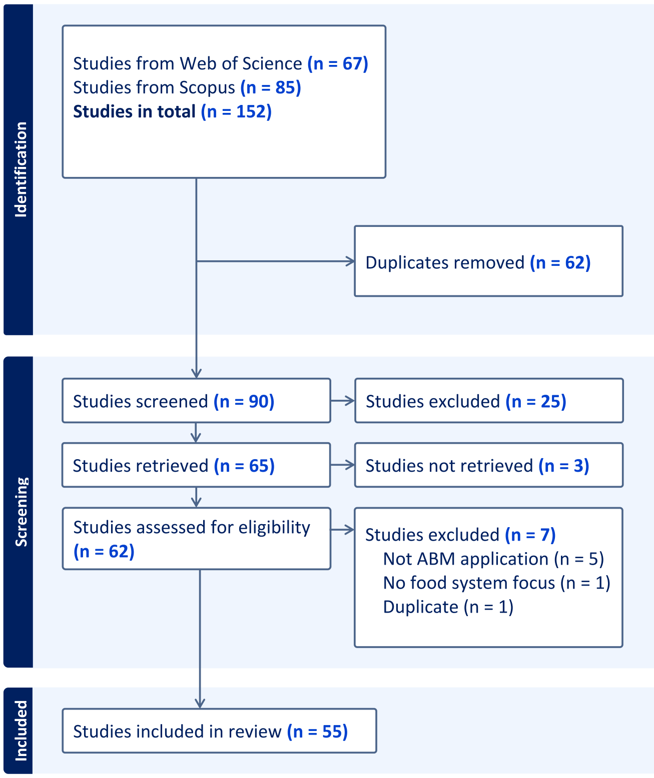

Fig. 2. Study selection process following PRISMA guidelines. Publications were identified using precise search terms to support transparency and reproducibility.

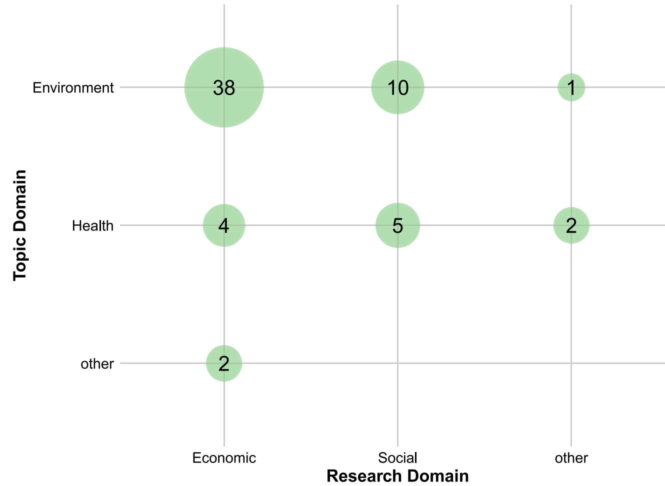

Fig. 3. Topic and research domains in ABM applications for food system modelling. Seven of the 55 included papers address both economic and social domains and are therefore counted in both categories.

application of an ABM within this context. Exclusion criteria are limited due to the precision of the search query. We exclude publications that do not involve an applied ABM, such as model proposals, literature reviews, theoretical explorations, or methodological discussions. Given the limited number of results, no additional thematic restrictions are imposed.

Following the steps set out in Fig. 2, we began with 152 studies identified on Web of Science (n = 67) and Scopus (n = 85) at the end of October 2024. After removing 62 duplicates, 90 papers remained for the screening process. A double-blind screening of the title, abstract, and keywords of these 90 papers resulted in the unanimous exclusion of 25 papers. During the full-text and data extraction process, which was conducted by a single author, 3 papers were unavailable despite attempts to contact the corresponding authors. Consequently, 62 papers proceeded to full-text review. Of these, 7 were excluded: 5 for not applying an ABM, 1 for lacking a food system context, and 1 as a duplicate of a previously submitted conference paper. This process resulted in 55 papers being included in the review. As this is a scoping review rather than a systematic literature review, the number of included publications is considered sufficient to identify research gaps. In terms of scope, it is situated within the mid-range of previously published scoping reviews (Tricco et al., 2016). The .ris files for the identified, screened, and included publications are provided as supplementary material. The list of included publications used for the data extraction are presented in the Appendix A in Table A.1.

4.3. Results

4.3.1. General findings and research practices in ABMs

First, we examine the metadata, focusing on publication trends over time. In Appendix A Fig. A.1, we observe that the largest share of publications are journal articles, followed by conference proceedings, and lastly, book chapters. Among the included studies, the oldest paper dates back to 2003, while the highest number of publications originate from 2020. After 2020, there is a noticeable decline, potentially attributable to the COVID-19 pandemic, followed by another peak in 2023. However, it is important to note that this scoping review is based on a limited number of publications. As a result, these macro-level trends are highly sensitive to a small number of observations and should therefore be interpreted with caution.

Another insight from the extracted data relates to how the publications position themselves within the research landscape. In Section 2, we distinguished between two fields commonly used to motivate research on food systems. First, there is the environmental focus, which examines the sustainability and adaptation of food systems in response to increasingly severe weather phenomena and climate change. Second, there is the health perspective, which focuses on ensuring sufficient nutrition for a growing global population.

On the other hand, we also categorized the research domains based on the perspective used to research these challenges, distinguishing between economic and social approaches. As shown in Fig. 3, the largest share of publications (38 in total) are in the domain of environmental economics. Additionally, ten papers apply social science methods to investigate environmental issues in food systems using ABMs. Thus, the majority of publications are motivated by environmental concerns. In terms of the health focus, a total of eleven papers were identified, of which four adopt an economic approach, five use a social perspective, and two remain uncategorized.

A critical aspect in developing ABMs is to accurately report the model specification. This applies not only to decision-making processes but also to all general aspects of model design. In Section 3, we introduced two commonly applied protocols: ODD and ODD + D, where the latter has a particular focus on decision-making processes. First and foremost, using a protocol when developing ABMs is essential for improving the understanding and reproducibility of the model. Furthermore, adopting a standardized protocol structure, such as ODD or ODD + D, facilitates comparability between studies.

In Fig. 4, we observe that less than half of the papers specify a protocol for their ABMs. Among these, the majority use the ODD protocol, followed by individually specified protocols grouped under "others", and ODD + D. The significant number of papers that do not employ any protocol is concerning and highlights the need for standardized protocols in future publications. In addition, Fig. A.3 illustrates the distribution of protocol usage across different journal topics. We observe that the main focus of the selected papers lies within journals

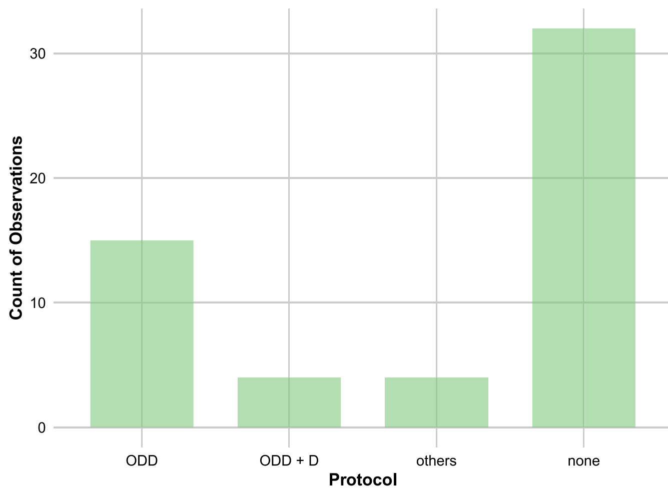

Fig. 4. Protocols used to improve transparency and reproducibility in the reviewed ABM studies.

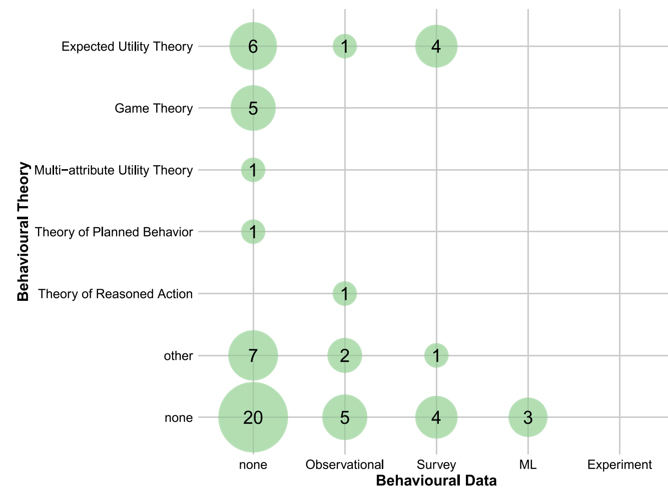

Fig. 5. Overview of behavioural theories and data types used to inform ABMs in food system modelling. Some studies incorporate more than one theory or data source. (ML = Machine Learning).

on environment and sustainability. Regarding protocol usage, no clear pattern emerges across journal categories, as publications without a specified protocol appear in all fields. In the category on modelling and simulation, a higher adoption of standardized protocols would typically be expected. However, the prevalence of conference proceedings in this journal category may counteract the expected higher use of such protocols.

These protocols capture not only aspects such as agent type, resolution, and time frame but also factors that influence decision-making. For example, they address how decision-making is shaped by adaptation, learning, location, time, and uncertainty, as well as the domains of influence on decision-making. As discussed in Section 3, the driving factors include economic concerns, environmental impacts and influences, and social impacts and influences. The corresponding Fig. A.4 illustrates that economic concerns are particularly influential in decision-making. This aligns with the majority of papers focusing on environmental economics. Beyond this, we observe a fairly even distribution across the various combinations of individual decision-making factors and influence domains.

Regarding model estimation, the mathematical implementation is typically based on an optimization, heuristic, or stochastic approach. As shown in Fig. A.5, the majority of papers use a stochastic approach, either alone or in combination with other methods. For model validation and calibration, we observe that approximately half of the reviewed papers include this step, while the other half do not (Fig. A.6).

4.3.2. Behavioural assumptions and resolution in ABMs

The decision-making process in ABMs is central to the modelling approach and should ideally be informed by either behavioural theory or behavioural data. Hence, we argue that ABMs development should be based on a theoretical foundation or an empirical foundation regarding agent behaviour. Ideally, both would inform the model. In Section 3, we mentioned EUT, Game Theory, and TPB as behavioural theories and rationality and bounded rationality as behavioural paradigms. However, during the data collection process, we expanded the range of theories to include Multi-attribute Utility Theory, and the Theory of Reasoned Action. Regarding behavioural data, we consider observational, survey, experimental, and machine learning data.

A striking finding in Fig. 5 is that 20 out of 55 reviewed publications do not base the decision-making processes in their ABMs on either behavioural theory or behavioural data. Given that ABMs are inherently dependent on agent decision-making, this absence of behavioural information raises concerns regarding model validity and robustness. Among the studies that do justify behavioural assumptions, EUT is the most commonly applied theoretical framework. On the data side, observational and survey data are the most frequently used sources to inform agent behaviour. Notably, none of the studies in this review rely on experimental data, despite its potential for offering controlled, empirical insights into decision-making. Moreover, only nine publications combine both behavioural theory and data. The absence of this dual foundation in the majority of studies highlights an area for methodological improvement in the field. The underlying paradigms used in the publications are shown in Fig. A.2. It shows that 31 publications do not specify any behavioural paradigm, while the most commonly applied paradigm among those that do is bounded rationality.

Another crucial factor in ABMs is their resolution. Since ABMs are building on individual behaviour, it is essential to understand the details of the respective agents to effectively inform the model. Consequently, the larger the model, the greater its complicatedness. Based on the data we extracted, we analysed the resolution of ABMs across three key parameters.

First, the **food system perspective**, as illustrated in Fig. 1, can range from sector-specific, supply chain, and linkages to a full food system perspective. Complicatedness increases along this spectrum, with sector-specific models being the simplest and full food system models being the most complicated. It is also possible to have a linkages perspective with a sector-specific focus, where a particular sector is interconnected with environmental and/or societal factors. Second, the **spatial extent** is another dimension of resolution, reflecting the empirical area of the analysis. This can range from village or city-level studies to those conducted at the country, continent, or global extent. As with the food system perspective, complicatedness increases with the extent of the study area. Third, the **agents** in the model constitute another dimension of resolution. Aggregating agents, such as modelling at the household, community, or sectoral level, may reduce the number of agents and smooth out individual-level heterogeneity, thereby simplifying some aspects of the model, such as data requirements or behavioural representation using expected utility or cost–benefit analysis. Additionally, aggregation reduces the number of agents and variables in the model, thus lowering its complicatedness and, consequently, also its overall complexity.[4] However, if the goal

[4] While the relationship between complicatedness and complexity is not strictly linear, a reduction in complicatedness is in most cases associated with a reduction in overall complexity, and vice versa, an increase in complicatedness often leads to greater complexity (Sun et al., 2016).

Fig. 6. Resolution of ABMs by food system focus, spatial extent, and agent type. Some studies include multiple agent types (e.g. in Linkages and Village/City categories) as well as multiple focuses or spatial extents, and are therefore counted more than once.

is to realistically represent group-level decision-making, aggregation may introduce additional complicatedness and complexity. For example, modelling collective decisions within households or districts may require more sophisticated behavioural rules (e.g., negotiation, consensus-building, or role-based dynamics), depending on the social context. Thus, the relationship between agent aggregation and model complicatedness is not inherently positive or negative and depends strongly on modelling purpose and implementation choices.

The results regarding these three dimensions of resolution are presented in Fig. 6. For the food systems dimension, we have increasing complicatedness, from sector-specific models at the bottom to full food system models at the top. Regarding spatial extent, complicatedness grows with size, moving from left to right. From a general perspective, most papers are concentrated towards the lower-left area of the figure. This indicates that the majority of studies focus on sector-specific aspects at a spatial extent up to the country level. Specifically, the most common focus is on production at the municipality level, represented by a total of twelve publications. The second most prevalent focus is shared by supply chain and consumption modelling. Supply chain models are primarily applied at the municipality and country levels. Consumption-oriented studies, on the other hand, tend to use smaller spatial resolutions, with applications at the village or city level, and the largest share falling under the category "other". This category for spatial extent mainly includes toy models and simulations without a specific empirical context.

The third dimension, defined by the agents involved in decision-making, is represented in Fig. 6 using pie chart colours. A single study can include multiple agent types, such as households and firms. The data reveals a relatively balanced representation of the agent types, with the exception of sector agents, which are rarely utilized. Firms/farms and "other" agent types constitute a significant portion in the studies. Notably, during the data collection process it became clear that the "others" category frequently encompasses entities related to judicial power, such as governments.

5. Discussion & conclusion

When developing ABMs, the models fundamentally rely on individual behaviour to accurately simulate possible scenarios. As a result, ABMs are highly sensitive to behavioural assumptions, which can lead to significant variability in model outputs (Brown et al., 2021). We therefore argue that assumed behaviours in ABMs should be informed either by theoretical frameworks or by empirical data, such as surveys, experiments, or observational studies. However, our review reveals that many applied ABMs in food system modelling lack a clear explanation of the behavioural assumptions embedded within the models. First, the majority of publications does not specify any underlying behavioural paradigm, such as rationality or bounded rationality. Second, we find that 20 of the 55 reviewed publications do not reference any behaviour theory or data to inform the behavioural assumptions used in the model, while only nine publications draw on both theory and data.

While our review distinguishes between theory- and data-informed behavioural assumptions, it is important to acknowledge that these are not mutually exclusive or independent sources of justification. In many cases, theory is employed precisely because empirical data is unavailable. Conversely, the collection and interpretation of data is often guided by theoretical frameworks, which shape the types of behaviours considered relevant and the methods used to observe them. Thus, the relationship between theory and data in ABMs should be seen as closely linked, with each informing and shaping the other. Rather than treating theory and data as separate pillars, future ABM research may benefit from more integrative approaches, where theoretical insights guide empirical inquiry, and empirical findings refine theoretical assumptions.

To advance the field, future research should focus on developing ABMs with more robust and well-justified behavioural assumptions, leveraging both theoretical frameworks and empirical data. However, selecting the appropriate theory or collecting relevant data can be a challenging task. Regarding data, our results indicate that experimental data has not yet been used to inform behavioural assumptions in food system models employing ABMs. Experimental data can be a valuable tool for extracting behavioural insights in controlled environments and may therefore be well-suited for informing ABMs. This represents a promising avenue for future research.

In terms of identifying relevant theories to support ABMs, the MoHuB framework by Schlüter et al. (2017) provides useful guidance. It facilitates a systematic search across disciplines such as psychology, sociology, and anthropology, in addition to the more frequently used behavioural economic theories. This broader search and interdisciplinary application of theories can help develop more nuanced and accurate representations of human behaviour in ABMs, ultimately improving model performance.

Having addressed how behavioural assumptions are justified in ABMs in accordance to our first research question, we now turn to the second question on resolution of ABMs. Food systems are inherently complex, and the design of ABMs applied to them is shaped by three key factors: food system focus, spatial extent, and agent aggregation. As emphasized by Sun et al. (2016), ABMs should be “as simple as possible, as complicated as necessary” (Sun et al., 2016, p. 65). This parsimony principle might be helpful when balancing model scope and complicatedness.

Broadening the food system focus, for example, from a single production sector to the full food system, typically increases the number of interactions and components that need to be represented. This adds to the model’s complicatedness (i.e., the number of agents and variables), which in turn raises its overall complexity (Sun et al., 2016). Similarly, increasing the spatial extent from local to national or global levels introduces additional layers of heterogeneity and interaction, further complicating the model. While these expansions can provide more comprehensive insights, they also risk making models overly complex and difficult to manage. In line with the principle of parsimony, our review suggests that ABMs are often most effective when focused on specific food system components and smaller spatial extents.

Agent aggregation has a more context-dependent effect. In theoretical models, aggregation is often used to simplify the system by reducing the number of agents and interactions, which can lower both complicatedness and complexity. However, in empirical applications, aggregation may increase complexity. When the goal is to realistically represent group-level decision-making, such as within households or regions, more sophisticated behavioural representations may be required to reflect how decisions are made collectively. This includes mechanisms like negotiation, coordination, or role-based dynamics. Thus, while aggregation can serve as a useful simplification in theory-driven models, it may introduce additional complexity when aiming for empirical realism.

Given this variation in model design and complexity, ensuring transparency and comparability across ABMs becomes essential. To enhance comparability while maintaining flexibility, it would be beneficial to clearly communicate the underlying model structures and purposes through a standardized protocol. The most commonly applied protocol in the reviewed publications is the ODD framework by Grimm et al. (2010). However, there is also a need for a similar framework to explicitly explain behavioural assumptions, including the decision-making rules of agents. The decision-making process can involve a complex interplay between personal abilities, such as learning, adapting, and observing, and the topics and domains relevant to these abilities, such as economic or social considerations. To capture and describe this complex decision-making process, the extension by Müller et al. (2013) of the ODD protocol, the ODD+D, provides a valuable tool for systematically describing these aspects. The ODD + D, has the most promising properties and can simplify reproducibility, thus supporting comparability.

This can also benefit studies such as systematic and scoping reviews. A key limitation in our data collection was that many of the variables we aimed to extract were not clearly communicated, which may have introduced biases. To improve comparability, and therefore also future reviews on ABMs, we suggest adopting ODD+D as a standard protocol in ABMs research focused on food systems.

In conclusion, this scoping review highlights several key issues in ABMs applied to food system modelling. Based on these findings, we propose a set of tentative guidelines that could serve as a starting point for ABM development:

- **Behavioural justification.** Assumptions about agent behaviour should be clearly justified. Ideally, they should be grounded in behavioural paradigms, supported by relevant theory, or informed by empirical data (e.g., from surveys, experiments, or observational studies). Where possible, a combination of theory and data is encouraged. The MoHuB framework by Schlüter et al. (2017) offers useful guidance for identifying relevant behavioural theories across disciplines.
- **Model parsimony.** ABMs should follow the principle of parsimony — “as simple as possible, as complicated as necessary” (Sun et al., 2016, p. 65). Our review suggests that this is best achieved by narrowing the focus to specific parts of the food system (e.g., production, distribution, consumption) and limiting the spatial extent to the smallest scale possible to answer the research question.
- **Transparency and documentation.** To promote reproducibility and comparability across studies, the use of standardized documentation protocols is essential. We recommend adopting the ODD + D protocol, which extends the established ODD framework by including details on human decision-making processes.

These proposed guidelines are not meant to be all-encompassing or definitive but may serve as a useful starting point for further discussion and development within the ABM and food systems research communities.

An additional point not specifically addressed in this scoping review, and therefore not included in the list above, is the importance of clearly stating the model’s purpose, as discussed by Edmonds et al. (2019), Brown et al. (2013). They emphasize that explicitly defining a model’s purpose is critical for evaluating its quality and relevance. Many models are developed without a clearly stated aim, which makes it difficult to assess their performance and usefulness (Edmonds et al., 2019). While the ODD protocol provides a useful structure for documenting models, Edmonds et al. (2019) argue that greater emphasis should be placed on articulating the intended purpose. This can range from prediction, explanation, and description to theoretical exposition, illustration, analogy, or social learning. Each purpose carries different risks and calls for distinct mitigation strategies. A clear understanding of the modelling purpose is therefore essential for managing potential pitfalls in model development and application.

Following the words of Box and Draper (1987), “all models are wrong, but some are useful”, we must understand when ABMs are useful. Models are always simplifications designed to help us better understand certain processes, but they can never fully capture the complexity of the real world. ABMs attempt to model individual behaviour to understand larger-scale dynamics (Castelli et al., 2024; Wilensky, 2015). Therefore, if an ABM is to be used, it is crucial to correctly understand individual decision-making and behaviour. Furthermore, ABMs are particularly effective at incorporating multidisciplinary knowledge and relating the model to external factors of food systems, such as environmental and social perspectives. Hence, if these points are fulfilled for the research project, ABMs can be a very good choice. However, if information on individual behaviour is limited, it may be more useful to explore other approaches, such as general equilibrium models or integrated assessment models, which do not follow a bottom-up approach but can be very useful for investigating macroeconomic effects and policies (Castelli et al., 2024).

As with any scoping review, the credibility of our findings depends on the scope and quality of the selected sample. We used a precise search query to ensure transparency and reproducibility. This approach simplifies the selection process by reducing the number of studies that require manual exclusion, thereby minimizing potential biases introduced by inconsistent author judgements. Additionally, it helps ensure that readers can easily trace the inclusion and exclusion of studies. However, we acknowledge the trade-off between precision and inclusiveness. Using strict search terms may limit the breadth of the review and potentially introduce bias towards studies that explicitly use the term "agent-based model" rather than alternative terminology such as "multi-agent simulation". As a result, some relevant studies may not have been captured.

While our review offers insights into how behavioural theory and data are used in ABMs of food systems, we recognize that it may not be exhaustive. Furthermore, although some of the identified issues, such as limited justification of behavioural assumptions, may plausibly extend to ABM applications in other research areas, our review was limited to the food system context. We therefore do not draw conclusions beyond this domain. Future research may explore whether similar patterns emerge in related fields. We also recommend that future systematic reviews adopt broader search strategies to validate and extend our findings, including alternative terms and sources that may capture a wider range of ABM applications.

CRediT authorship contribution statement

Alexander Öttl: Writing – review & editing, Writing – original draft, Visualization, Formal analysis, Data curation, Conceptualization. **Mette Termansen:** Writing – review & editing, Supervision, Project administration, Funding acquisition, Data curation, Conceptualization.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used ChatGPT by OpenAI in order to improve readability and language. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Declaration of competing interest

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

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Appendix A

See Figs. A.1–A.6 and Table A.1.

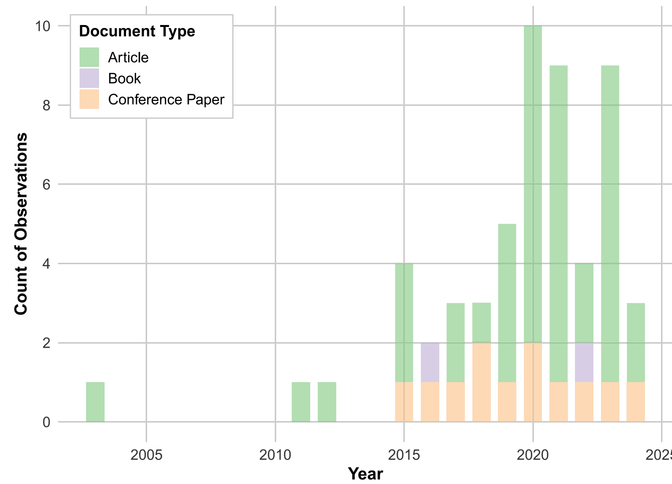

Fig. A.1. Publication trends over time in ABM applications for food system modelling.

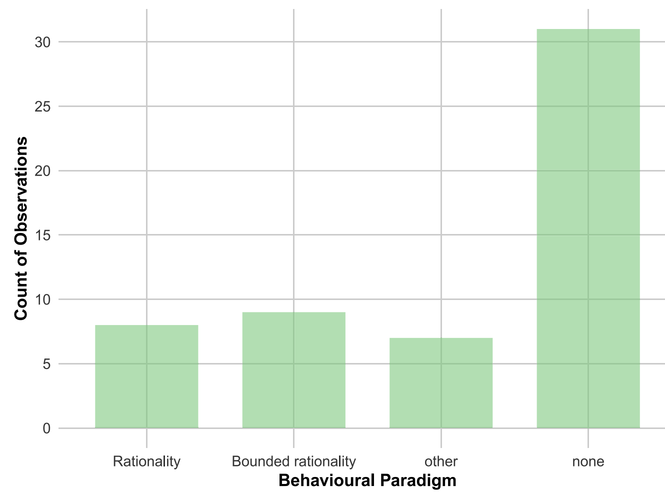

Fig. A.2. Count of behavioural paradigms applied in ABMs reviewed in this scoping study.

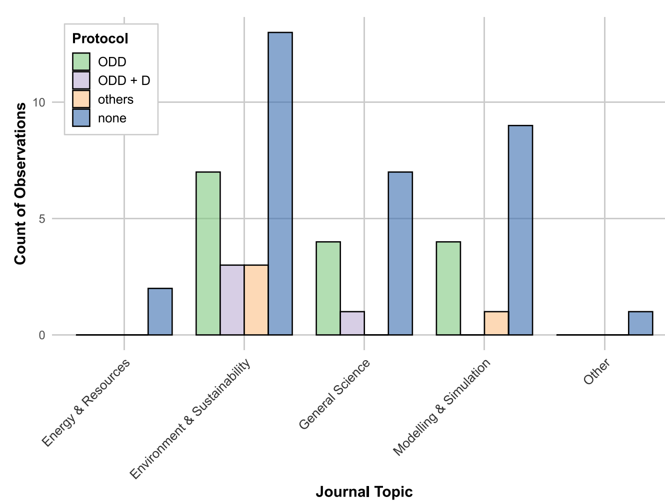

Fig. A.3. Classification of articles by journal topic and protocols. Journal topic categories were manually assigned to each journal or proceeding. The detailed categorization is documented in the `ABM_review_figures.R` file.

Table A.1
Author and title list of included publications in data extraction.

Author	Title
Abel and Faust (2018)	Modeling Food Desert Disruptors: Impact of Public Transit Systems on Food Access
Anggraeni et al. (2021)	Role of Artificial Intelligence in the Management of Food Waste
Angourakis et al. (2020)	How to 'downsize' a complex society: an agent-based modelling approach to assess the resilience of Indus Civilisation settlements to past climate change
Blok et al. (2015)	Reducing Income Inequalities in Food Consumption Explorations With an Agent-Based Model
Bora and Krejci (2015)	An agent-based model of supplier management in regional food systems (WIP)
Brady et al. (2012)	An agent-based approach to modeling impacts of agricultural policy on land use, biodiversity and ecosystem services
Brown et al. (2021)	How modelling paradigms affect simulated future land use change
Collins and Krejci (2020)	Understanding the impact of farmer autonomy on transportation collaboration using agent-based modeling
Craven and Krejci (2017)	An agent-based model of regional food supply chain disintermediation
Craven and Krejci (2016)	Assessing management strategies for intermediated regional food supply networks
Etherton et al. (2023)	Are avocados toast? A framework to analyze decision-making for emerging epidemics, applied to laurel wilt
Falconer et al. (2020)	Anaerobic Digestion of food waste: Eliciting sustainable water-energy-food nexus practices with Agent Based Modelling and visual analytics
Fernandez-Mena et al. (2020)	Co-benefits and Trade-Offs From Agro-Food System Redesign for Circularity: A Case Study With the FAN Agent-Based Model
Fonteijn et al. (2024)	DARTS: Evolving Resilience of the Global Food System to Production and Trade Shocks
Ge et al. (2021)	Food and nutrition security under global trade: a relation-driven agent-based global trade model
Gonzalez-Redin et al. (2020)	Exploring sustainable scenarios in debt-based social-ecological systems: The case for palm oil production in Indonesia
Guo et al. (2020)	Multi-level system modelling of the resource-food-bioenergy nexus in the global south
Hennessy et al. (2022)	Using models to understand community interventions for improving public health and food systems
Innocenti et al. (2022)	Agent-based modelling of a small-scale fishery in Corsica
Khan et al. (2017)	A coupled modeling framework for sustainable watershed management in transboundary river basins
Kunz et al. (2023)	Adoption and transferability of joint interventions to fight modern slavery in food supply chains
Ligmann-Zielinska et al. (2016)	The impact of urban form on weight loss: Combining a spatial agent-based model with a transtheoretical model of health behavior change
Lloyd and Chalabi (2021)	Climate change, hunger and rural health through the lens of farming styles: An agent-based model to assess the potential role of peasant farming
Mayangsari et al. (2024)	Simple Heuristics as Mental Model for Staple Food Choice: An ABM Exercise
McPhee-Knowles (2015)	Growing Food Safety from the Bottom Up: An Agent-Based Model of Food Safety Inspections
Mittal et al. (2019)	An Agent-Based Model of Surplus Food Rescue using Crowd-Shipping
Mokhtari and Van Doren (2019)	An agent-based model for pathogen persistence and cross-contamination dynamics in a food facility
Molajou et al. (2021)	Incorporating Social System into Water-Food-Energy Nexus
Namany et al. (2024)	Competition vs. cooperation: An agent based model for sustainable tomatoes' import system
Namany et al. (2022)	Developing intelligence in food security: An agent-based modelling approach of Qatar's food system interactions under socio-economic and environmental considerations
Namany et al. (2020)	Sustainable food security decision-making: An agent-based modelling approach
Naqvi et al. (2020)	The risk and consequences of multiple breadbasket failures: an integrated copula and multilayer agent-based modeling approach
Ng et al. (2003)	Co-evolutionary processes in supply chain networks
O'Hare (2023)	A toy model of food production in a connected landscape
Patel et al. (2023)	An Agent-Based Model of Agricultural Land Use in Support of Local Food Systems
Pérez-Salazar et al. (2019)	An Agent-Based Model Driven Decision Support System for Reactive Aggregate Production Scheduling in the Green Coffee Supply Chain
Phetheet et al. (2021)	Relating agriculture, energy, and water decisions to farm incomes and climate projections using two freeware programs, FEWCalc and DSSAT
Python Ndekou et al. (2023)	An agent-based model for collaborative learning to combat antimicrobial resistance: proof of concept based on broiler production in Senegal
Sadeghiamirshahidi et al. (2021)	An Agent-Based Model of Digitally-Mediated Farmer Transportation Collaboration
Schlüter et al. (2021)	The interplay between top-down interventions and bottom-up self-organization shapes opportunities for transforming self-governance in small-scale fisheries
Shaaban et al. (2023)	Understanding the future and evolution of agri-food systems: A combination of qualitative scenarios with agent-based modelling
Shastri et al. (2011)	Agent-Based Analysis of Biomass Feedstock Production Dynamics
Staccione et al. (2023)	Exploring the effects of protected area networks on the European land system
Taghikhah et al. (2020)	Exploring consumer behavior and policy options in organic food adoption: Insights from the Australian wine sector
Tavares et al. (2024)	The influence of pricing interventions in food choices on Brazil: An agent-based modelling approach

(*continued on next page*)

Table A.1 (*continued*).

Author	Title
Thomopoulos and Bakalis (2018)	Consumer demand for sustainable versus low-cost food products: An agent-based modelling approach
Thomopoulos et al. (2021)	Reduced meat consumption: from multicriteria argument modelling to agent-based social simulation
Thompson et al. (2021)	Iowa Urban FEWS: Integrating Social and Biophysical Models for Exploration of Urban Food, Energy, and Water Systems
Trieu and Lin (2022)	The Development of a Service System for Facilitating Food Resource Allocation and Service Exchange
Tsai et al. (2015)	An interactive land use transition agent-based model (ILUTABM): Endogenizing human–environment interactions in the Western Missisquoi Watershed
Wens et al. (2020)	Simulating Small-Scale Agricultural Adaptation Decisions in Response to Drought Risk: An Empirical Agent-Based Model for Semi-Arid Kenya
Yang et al. (2018)	Quantifying the Sustainability of Water Availability for the Water-Food-Energy-Ecosystem Nexus in the Niger River Basin
Yuan et al. (2017)	Assessing the impacts of the changes in farming systems on food security and environmental sustainability of a Chinese rural region under different policy scenarios: an agent-based model
Zhu et al. (2023)	Agent-Based Modeling for Water-Energy-Food Nexus and Its Application in Ningdong Energy and Chemical Base
Zia et al. (2019)	Agent-Based Modeling of a Self-Organized Food Safety System

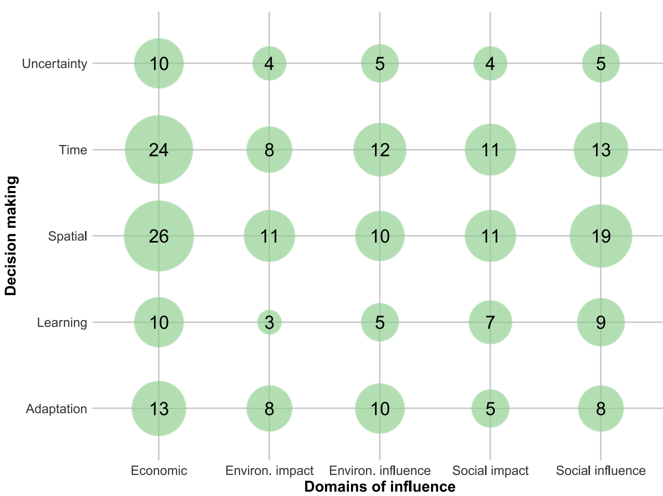

Fig. A.4. Decision-making and influence domains represented in ABMs reviewed in this scoping study. The figure distinguishes between how agents make decisions (learning, adaptation, etc.) and the domains that influence those decisions, following the framework adapted from Groeneveld et al. (2017) and Müller et al. (2013).

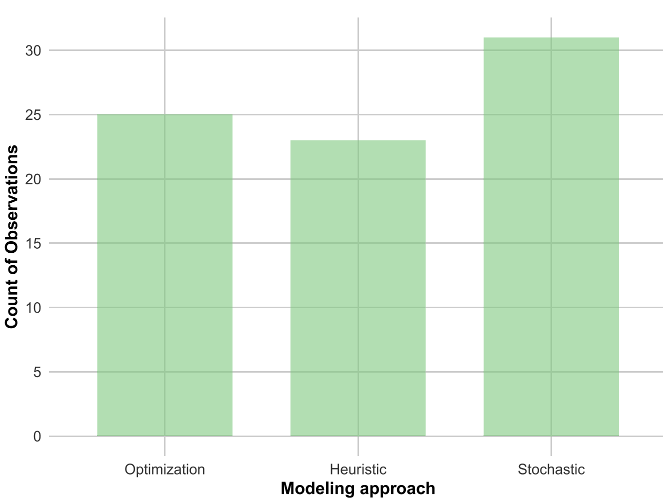

Fig. A.5. Mathematical implementation approaches in the reviewed ABM studies.

Appendix B. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.envsoft.2025.106617.

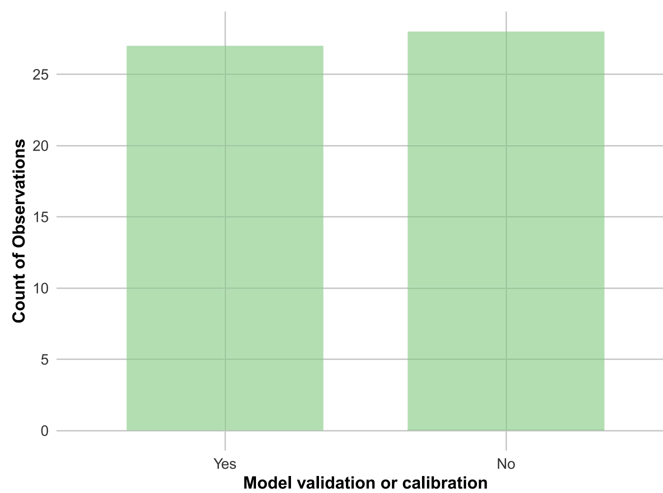

Fig. A.6. Inclusion of model validation or calibration in the reviewed ABM studies. A study is marked "yes" if it includes either validation or calibration.

Data availability

Data is made available with publication in supplementary material.

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