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REVIEW ARTICLE

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Agent-based modeling and simulation for economic markets: a comprehensive review of applications, challenges, and opportunities

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ABSTRACT
Economic and financial markets are characterized by interactions among various entities, whose individual behaviors and decisions collectively lead to emergent phenomena that may be unapparent and unexpected. A well-known approach for developing detailed models that closely represent such dynamic and complex systems is Agent-based Modeling and Simulation (ABMS). This comprehensive review analyzes the state-of-the-art application of ABMS for economic and financial market analysis, examining over 120 studies to provide a clear understanding of its current state and future potential. The review demonstrates how simulating market behavior with agent-based models can enhance understanding of market dynamics and serve as a robust decision-support system for running “what-if” scenarios and exploring their outcomes in a virtual environment. Furthermore, it critically assesses methodological challenges and highlights future opportunities for employing ABMS to analyze economic and financial markets.

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1. Introduction

Agent-based modeling and simulation (ABMS) is an approach that represents complex systems as collections of autonomous decision-making entities called agents, simulating their interactions to analyze the emergence of complex behaviors at various spatio-temporal resolutions, as well as macro-level phenomena that mirror the original system. These agents can represent economic actors such as firms, consumers, or traders where each agent is given behavioral rules that govern their decision-making and interactions with other agents and the environment. ABMS can generate macro-level patterns and dynamics that emerge from the bottom by simulating the micro-level behaviors and interactions of many individual agents (Tesfatsion, 2006). This bottom-up approach enables ABMS to capture emergent phenomena that arise from the interactions of individual agents, which makes it well-suited for studying markets and other complex adaptive systems (Farmer & Foley, 2009). Dosi and Roventini (2019) highlight the limitations of traditional DSGE (dynamic stochastic general equilibrium) models and point out their reliance on unrealistic assumptions and post-hoc adjustments to match empirical data. In contrast, ABMS offers a more flexible and realistic approach to economic modeling. For instance, an agent-based stock market model can simulate individual investors making decisions based on diverse strategies and reveal how market trends emerge from the collective actions of investors.

Several key advantages of ABMS make it practical to analyze economic and financial markets: ABMS can represent heterogeneous market participants with diverse strategies and behaviors; agents can have bounded rationality and limited information in contrast to assumptions of perfect rationality in many traditional economic models; ABMS enables modeling direct interactions between agents; exploring out-of-equilibrium dynamics and the possibility of emergence of multiple equilibria; incorporating realistic institutional structures and policies; integrating insights from behavioral economics; and flexibility to test different hypotheses about market mechanisms (Arthur, 2021; LeBaron, 2006; Tesfatsion, 2006). Generally, the economy is a complex, evolving system with heterogeneous agents interacting in non-equilibrium conditions. These properties align with the ABMS approach and its potential to provide more nuanced insights into economic phenomena (Dosi & Roventini, 2019).

Over the past few decades, ABMS has been applied to study various aspects of economic and financial markets, including economic forecasting (Poledna et al., 2023), pricing strategy and inventory management (Abdolhosseini et al., 2023), financial market mechanism (Fischer & Riedler, 2014), regulatory policy effect (Leal & Napoletano, 2019), and new product

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market diffusion (Rand & Stummer, 2021). For example, ABMS has provided insights into phenomena such as the origin of stylized facts in financial markets (Alfi et al., 2009), the impact of high-frequency trading (Paddrik et al., 2012), and the impact of information delay and liquidity on financial market stability (Zhou et al., 2022). Haldane and Turrell (2018) argue that macroeconomics has become overly isolated and could benefit from incorporating techniques and insights from other disciplines, particularly ABMS. In their paper, the authors presented ABMS as a promising complementary approach to traditional macroeconomic modeling and highlighted the potential of this approach to capture the complexity of economic systems by allowing for heterogeneous agents, non-linear interactions, and emergent phenomena. They call for greater openness to interdisciplinary approaches in macroeconomics, emphasizing the potential benefits of ABMS in understanding and analyzing market dynamics, financial stability, and policy effects. Moreover, recent advancements in computational capabilities mainly driven by Moore's law (Nagy et al., 2011) made employment of large agent-based models more practical (Axtell & Farmer, 2025). Finally, the availability of more granular data made ABMS even more suitable for market analysis and prediction. This convergence of factors has led to a significant increase in ABMS research in economics and finance. The growing interest in ABMS for market analysis is reflected in the increasing number of publications in the field over the past two decades. Figure 1 illustrates the trend in journal publications related to ABMS in economics and finance from 2004 to 2024. The data presented in this Figure is obtained through a systematic search in the Scopus database. We designed the search criteria to capture journal articles that discuss ABMS in the context of economics, finance, or markets, published between 2004 and 2024. As shown in Figure 1 (see also An et al. (2021) and Vincenot (2018)), there has been a consistent upward trend in the number of publications in ABMS for exploring market dynamics, which underscores the growing interest of ABMS as a valuable tool in this field.

While several comprehensive reviews have examined the development of ABMS in economics (e.g., Axtell and Farmer (2025); Tesfatsion (2023); Chen et al. (2012)), these works primarily focus on historical evolution, theoretical foundations, or specific subfields such as financial econometrics. There remains a need for a systematic categorization that bridges these theoretical foundations with practical, problem-oriented decision areas.

Moreover, despite growing interest in ABMS for exploring market dynamics, there is a need for a comprehensive review to examine its diverse applications, key challenges, and future opportunities in market analysis (discussed in Section 4). This paper aims to address this gap by focusing on three primary Research Questions (RQs):

- **RQ1**: What are the key decision areas within economic and financial markets where ABMS has been successfully applied?
- **RQ2**: What are the methodological challenges and opportunities associated with using ABMS for market analysis?
- **RQ3**: How can ABMS evolve to address emerging challenges, particularly through integration with new technologies?

The remainder of the paper is structured as follows: Section 2 provides a general background on the design and development of agent-based models. To answer RQ1, Section 3 presents our two-stage review methodology for categorizing the literature into decision

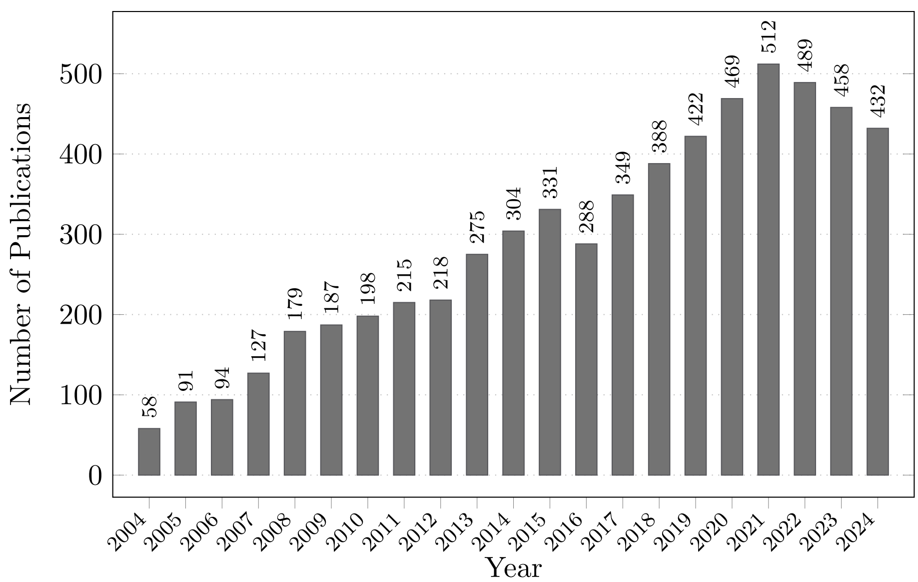

Figure 1. Journal publications in agent-based modeling and simulation in economics and finance (2004–2024).

areas where ABMS can serve as a decision-support system in economics and finance, offering a structured view of these studies. We selected well-established research for each category to exemplify how they employed ABMS. Each research presentation is based on the Overview component of the ODD (Overview, Design concepts, and Details) protocol (Grimm et al., 2006) to ensure consistency in our analysis. RQ2 and aspects of RQ3 are addressed in Section 4, which details common and category-specific challenges and opportunities of employing ABMS and presents a holistic perspective on ABMS's current state and future potential in market analysis. Finally, RQ3 is fully synthesized in Section 5, which summarizes our findings and provides an outlook for future research on the application of ABMS for market analysis. This paper bridges theoretical foundations with practical applications and future directions, serving as a valuable resource for advancing the understanding and application of ABMS in economics and financial markets research.

2. Design and development of agent-based models

This section provides an overview of the key aspects of designing and developing agent-based models. This overview begins with examining the fundamental structure of agent-based models, followed by exploring various sources of inspiration and approaches for model design. Finally, we introduce useful resources to find the practical tool or framework for implementing agent-based models.

Over the past 20 years, several papers have provided excellent resources for those beginning to explore ABMS, and here we mention some notable ones that inspired various studies in chronological order. Bonabeau (2002) presents the key benefits of ABMS and a detailed examination of ABMS applications across various domains while offering insights into the conditions under which ABMS is most advantageous for complex system analysis. In a later study by Macal and North (2005), the authors provide a comprehensive tutorial that describes the theoretical and practical foundations of ABMS while providing insights into the relationship between ABMS and traditional modeling techniques, such as Equation-Based Modeling, System Dynamics, and DSGE. Helbing and Balietti (2010) discuss the potential of ABMS for understanding complex socio-economic systems while outlining the steps involved in developing rigorous agent-based models, and address key challenges and best practices in the field. Axelrod and Tesfatsion (2016) present a comprehensive online guide for newcomers to ABMS in the social sciences, where they provide curated readings, demonstration software, and resources across various topics in ABMS such as complexity, emergence, evolution, learning, norms, markets, and networks. Lastly, Railsback and Grimm (2019) provide a comprehensive introduction to ABMS for scientists and students in their book. Their book offers practical guidance on designing, implementing, and analyzing agent-based models using NetLogo software while covering key concepts and techniques in ABMS, emphasizing their application across various scientific disciplines.

2.1. Agent-based modeling structure

The structure of agent-based models is fundamental to their design and implementation. Figure 2 illustrates the key elements and relationships that typically constitute agent-based models. This structured representation of agent-based models can systematically consider all essential elements and provide a framework for understanding and developing them across various domains.

Agents are the autonomous, decision-making entities of agent-based models and can represent a wide range of actors, from individuals to organizations, depending on the system being modeled. In this context, "autonomous" implies that agents operate without a central controller dictating their individual actions step-by-step, even if their internal decision rules are deterministic. Agents are defined by their Type (reflecting system heterogeneity), Characteristics (which may be static properties or dynamic attributes that evolve over time), and Behavior. Agent behavior is defined by

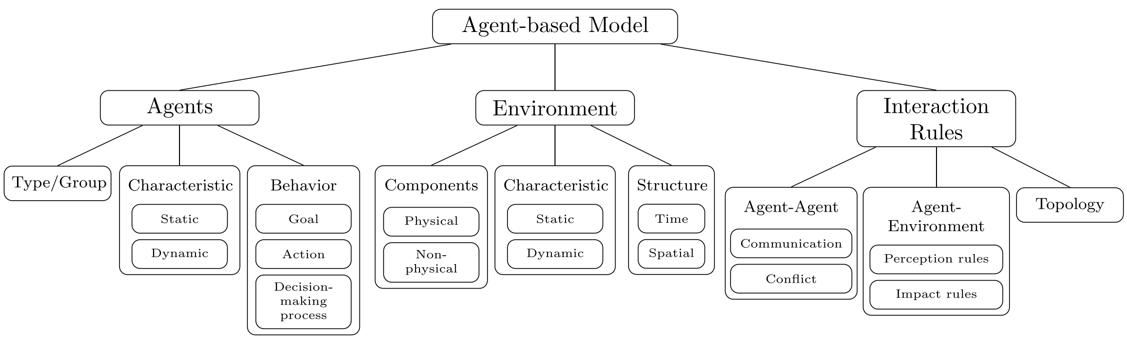

Figure 2. Structure of an agent-based model.

the interplay of goals (the objective function), decision-making processes (the mechanism or logic), and actions (the observable output). While these components are distinct, their implementation varies across architectures; for instance, in complex BDI (Belief-Desire-Intention) frameworks, goals are explicit state variables (Georgeff & Rao, 1991), whereas in simple reactive architectures, goals may be implicit in the decision rules (e.g., survival rules). Goals drive the actions, and actions are specific activities agents can perform within the model to achieve their goals. Decision-making processes are the cognitive mechanisms or algorithms that guide agent choices and responses.

The second main element of agent-based models is Environment in which agents operate, and it can be defined by its Components, Characteristics, and Structure. Components can be physical (e.g., infrastructure) or non-physical (e.g., institutional rules). The environment possesses static or dynamic characteristics and is structured by temporal frameworks and spatial layouts (geographical or topological).

Interaction rules govern how different elements of the model interact. Agent-agent interactions define rules for inter-agent communication and conflict resolution. Agent-environment interactions are typically governed by perception rules (or sensing mechanisms), which determine how agents gather information about their surroundings, and impact rules that define how agent actions affect the environment. The Topology of interactions describes the underlying structure that defines how agents and environmental components are connected or related.

2.2. Design of agent-based models

Multiple approaches are used to design and develop agent-based models, significantly influencing the model's characteristics, accuracy, and applicability. Here, we review multiple approaches that contribute to the design and development of agent-based models, each offering unique perspectives for capturing the complexities of the model's subject.

2.2.1. Top-down vs bottom-up

Generally, the top-down approach begins with the specification of the global system state while assuming each entity has global knowledge. However, the nature of the ABMS suggests a shift from traditional top-down modeling approaches. ABMS allows modelers to explicitly represent individual agents and their interactions instead of aggregating agents into abstract variables like abundance (Railsback & Grimm, 2019). The bottom-up approach begins with specifying the requirements and capabilities of individual entities of the system, with the global behavior emerging from interactions among these components and between components and their environment (Crespi et al., 2008). Macal and North (2005) in their tutorial paper, describe the bottom-up approach as starting with identifying agents and their attributes, behaviors, and interactions. The model is then executed, allowing system behavior to emerge from the aggregated individual agent behaviors. This approach contrasts with top-down approaches that begin with a defined system behavior and then attempt to deconstruct it into component parts. While ABMS shares the bottom-up philosophy with other modeling techniques such as microsimulation and Cellular Automata (CA), it offers distinct advantages for economic market analysis. Traditional microsimulation excels at capturing population heterogeneity and static policy impacts but often lacks explicit agent-to-agent interaction mechanisms necessary to model contagion or social learning (Richiardi, 2014). Similarly, while CA captures local interactions through fixed grid topologies, it is typically constrained by static spatial structures and simplistic state-transition rules. In contrast, ABMS allows for mobile agents, dynamic network structures, and complex adaptive decision-making processes (Batty, 2005). These capabilities are particularly suited for capturing transient dynamics and emergent behaviors in economic systems and enable researchers to relax classical equilibrium assumptions and investigate the dynamic paths markets take over time (Macal & North, 2005). Crespi et al. (2008) compare top-down and bottom-up design approaches and highlight key differences of these approaches for developing multi-agent systems through a case study. In practice, the bottom-up approach involves several key steps: identifying agents and their attributes, defining agent behaviors and decision rules, specifying how agents interact with each other and their environment, implementing the model, and observing emergent patterns. Railsback and Grimm (2019) emphasize the importance of starting with the simplest possible model and focusing on the minimum number of essential factors. This approach aligns with the bottom-up philosophy of beginning with basic agent-level behaviors and allowing complexity to emerge naturally. Generally, the bottom-up approach allows modelers to directly encode hypotheses about agent behavior and explore resulting emergent properties. This approach also provides a more intuitive way to represent complex systems, especially when individual agent behaviors are well understood but system-level behaviors are not.

2.2.2. Pattern-oriented

Pattern-oriented modeling (POM) is an approach for designing and developing agent-based models that focuses on using multiple observed patterns from the real system to guide model structure, parameterization, and validation. This approach aims to create models that capture the essential mechanisms and structures of complex systems by reproducing key patterns observed at different hierarchical levels and scales. The POM approach provides a framework for addressing two main challenges in bottom-up modeling: complexity and uncertainty. POM helps modelers find an optimal level of model complexity—what Grimm et al. (2005) call the "Medawar zone" where model payoff is highest. The process of POM starts with identifying a set of observed patterns that characterize the system's behavior and are relevant to the modeling purpose. Then, the modeler uses these patterns to determine the model structure. Afterward, the modeler implements alternative submodels or theories for key processes and tests how well different model versions reproduce the observed patterns. Finally, modelers use the patterns to reduce parameter uncertainty through calibration or filtering.

Two notable research papers that exemplify the application of POM are the studies by Grimm et al. (2005) and Railsback and Johnson (2011). Grimm et al. (2005) introduce POM as a unifying framework for designing, testing, and analyzing bottom-up simulation models, specifically agent-based models. They showcase the approach using examples from ecological modeling, such as beech forest dynamics to demonstrate how multiple observed patterns can inform model structure and resolution. While this paper did not develop a specific agent-based model, it laid the theoretical groundwork for applying POM in various modeling contexts, including agent-based modeling. In the second study, Railsback and Johnson (2011) provide a concrete application of POM in developing a spatially explicit, individual-based model of birds foraging and pest control in coffee farms. They identified nine characteristic patterns from field observations, which guided their model's design and parameterization. Furthermore, they used these patterns to test alternative theories of bird foraging behavior to confirm how POM can be used not only for model development but also for theory refinement. These works illustrate the power of POM in creating structurally realistic models that can reproduce multiple observed patterns and generate credible predictions about complex systems.

2.2.3. Theory-driven

Theory-driven approaches ground the agent-based model structure, agent behaviors, and interaction rules in established theories from social and behavioral sciences. This approach aims to leverage existing theoretical frameworks to inform the key mechanisms and processes represented in the model. The theory-driven approach typically involves the following steps:

- Identifying relevant theories that can explain the phenomenon of interest.
- Translating theoretical constructs and relationships into computational rules and agent attributes.
- Implementing the theory-based rules in the agent-based model architecture.
- Validating model outputs against theoretical predictions and empirical data when available.

An influential example of a theory-driven ABMS is Axelrod (1997) cooperation model based on game theory, in which the author implemented theoretically derived strategies like tit-for-tat to study the evolution of cooperation. Following this foundational work, the conceptual status of theoretical models was further refined in the 2000s. Sugden (2000) argued that even without direct empirical data, theory-driven models function as parallel conceptual systems that allow researchers to make inductive inferences about real-world economic mechanisms based on the internal coherence and plausibility of the model logic. Building on this distinction, Phan and Varenne (2010) categorizes agent-based simulations into "conceptual explorations" versus "experiments", noting that theory-driven models primarily serve to test the consistency of theoretical constructs and the emergence of macro-phenomena from micro-rules.

By the next decade, the focus shifted toward validating these generative mechanisms. Conte and Paolucci (2014) discuss how theory-driven ABMS can provide a "generative explanation" of social phenomena by modeling the mechanisms proposed by theories. The authors argue that this approach allows testing theoretical hypotheses and exploring how macro-level patterns emerge from micro-level behaviors specified by theory. Practical applications also became more specific; for instance, Picascia (2014) utilizes the "Rent-Gap Theory" to define agent investment behaviors in urban regeneration scenarios and demonstrates how macro-level economic constraints formulated in theory can determine micro-level agent mobility.

More recently, Schlüter et al. (2017) formalize these approaches by proposing a framework for mapping behavioral theories into agent-based models' structures and rules. They demonstrate how theories can be systematically translated into agent decision-making processes. Finally, Taghikhah et al. (2021) presented a comparative case study of theory-driven versus data-driven ABMS in organic wine purchasing behavior, integrating multiple behavioral theories to specify agent attributes.

2.2.4. Data-driven

Data-driven ABMS employs empirical data to inform model structure, parameters, and behaviors rather than relying solely on theoretical assumptions or expert knowledge. This approach aims to create more realistic and accurate models by grounding them in real-world observations. Hassan et al. (2010) propose integrating empirical data into different stages of the agent-based models development process from initialization to parameter calibration and validation. They demonstrated how using census data to initialize agent attributes and derive behavioral probabilities could improve model realism compared to random initialization. Kavak et al. (2018) contribute to this field by exploring the integration of big data, agents, and machine learning in ABMS. They discussed potential methods for using individual-level data to generate agent behavioral rules and initialize agent attributes, though they did not propose a specific framework.

Janssen and Ostrom (2006) provide a valuable framework for understanding the integration of empirical methods with ABMS. They identify four key empirical approaches used to test agent-based models: case studies, stylized facts, role-playing games, and laboratory experiments. The authors discuss challenges in social science research, such as subject reflexivity and population representativeness, and how these impact agent-based modeling. They emphasize the need to balance generalizability with context-specificity and the trade-offs between an in-depth study of a few subjects versus a broader analysis of many. In a recent study, Jamali and Lazarova-Molnar (2024) present a comprehensive framework for data-driven ABMS. Their framework provides a systematic approach to incorporating data throughout the agent-based model development process. Moreover, they discussed how data-driven methods could contribute to each aspect of the model development process, from model development to model validation, by reviewing previous research in this field.

2.2.5. Hybrid

Hybrid approaches leverage the strengths of different approaches while mitigating their individual weaknesses. For example, a hybrid model might use theory to inform the overall structure and key mechanisms, while using empirical data to parameterize specific agent behaviors and attributes. This approach allows the model to be grounded in established theoretical frameworks while also capturing real-world complexity and heterogeneity. Several researchers have demonstrated hybrid approaches for ABMS. Robinson et al. (2007) describe how different empirical methods like surveys, participant observation, field experiments, and spatial data analysis can be combined to inform various components of agent-based models. They argue that integrating multiple data sources and methods allows for more comprehensive modeling of complex human-environment interactions.

Here, we mention two well-established studies that employed a hybrid approach to develop an agent-based model. The first one is done by Polhill et al. (2010), who discuss using qualitative evidence to enhance existing agent-based modeling frameworks. The authors described an iterative process of using field research data to suggest modifications and extensions to model structures and then checking those changes with respondents which allows for incremental improvements to models while maintaining empirical validity. The second study by Ghorbani et al. (2015) presents a methodology for using qualitative ethnographic research to inform the development of agent-based models. Their approach uses ethnographic data collection and analysis to identify key concepts, agent types, decision-making processes, and social dynamics. This qualitative understanding is then formalized into model structures and parameters. The authors demonstrated how this hybrid qualitative-quantitative approach can produce models that are both empirically grounded and theoretically sound.

2.3. Tools and frameworks for developing agent-based models

Various tools and platforms are available for developing agent-based models, catering to diverse needs across various disciplines and application domains. These range from general-purpose frameworks to specialized tools for specific types of simulations. Several comprehensive reviews have been conducted in recent years that compared and evaluated the features, capabilities, and user experiences of different ABMS development tools. These reviews offer valuable insights into the current landscape of ABMS tools and can serve as helpful resources for researchers selecting an appropriate platform.

Abar et al. (2017) conducted one of the most extensive reviews where the authors examined eighty-five ABMS tools across a wide range of characteristics, including programming language, graphical user interface capabilities, operating system support, ease of use, scalability, and licensing. Their detailed comparison provides a thorough overview of the features offered by each platform. In a later study, Pal et al. (2020) focus specifically on categorizing platforms as general-purpose vs. domain-specific and open-source vs. commercial. Their review provides historical context on the evolution of ABMS tools over time and highlights platforms tailored for particular application areas. Antelmi et al. (2022) took a more hands-on approach and evaluated a subset of popular open-source ABMS tools through the practical implementation of example models. They assessed factors like installation process, documentation quality, development effort required, and runtime performance. This experiential evaluation offers insights into the user experience of working with different platforms. Lastly, Wrona et al. (2023) updated and expanded on previous reviews, examining both long-standing and newly developed ABMS platforms. They organized tools into categories like general-purpose, cognitive/social, learning agents, and domain-specific simulations. Their review offers the most up-to-date picture of the current ABMS tool ecosystem.

3. Agent-based modeling and simulation of economic markets

Our systematic review follows a two-stage methodology. In the first stage, we conducted a broad search in Scopus using the search string [TITLE-ABS-KEY ("agent-based*" OR "agent based*") AND TITLE-ABS-KEY(econom* OR financ* OR market*)] to identify major areas where ABMS has been applied in market analysis. Scopus was selected as the primary database due to its extensive coverage of interdisciplinary fields, particularly bridging computer science and social sciences, which is essential for ABMS research. While distinct from economics-specific databases like EconLit, Scopus provides sufficient overlap with major economic journals to capture key modeling studies while ensuring broader coverage of computational advancements. Analysis of these results was conducted using an inductive thematic analysis. Initial search results were clustered based on the primary economic decision being modeled (e.g., "buying" behaviors were grouped into Consumer Behavior), followed by expert refinement to ensure the nine decision areas were distinct and comprehensive. This analysis revealed nine distinct decision areas where ABMS has demonstrated significant impact: (1) economic forecasting and market dynamics, (2) consumer behavior, (3) market penetration, (4) competition and pricing strategies, (5) financial market mechanisms and stability, (6) policy effects and regulatory impact, (7) innovation diffusion and market diffusion, (8) market vulnerability and crises, and (9) market impact and volatility. In the second stage, we conducted focused systematic searches for each decision area, combining ABMS terminology with area-specific keywords to identify influential papers. Our selection criteria balanced two objectives: identifying seminal works that have shaped each field (based on citation impact and methodological contributions) and including the most recent papers that demonstrate current developments and emerging approaches. This dual approach ensures our review captures both foundational research and state-of-the-art applications. Papers were selected based on citation impact for older works, methodological precision, and demonstrated practical applications, while recent papers were selected based on their novelty, methodological sophistication, and relevance to current market challenges.

To systematically analyze how ABMS has been applied across different market domains, we first examine previous literature reviews to identify gaps and establish the need for our comprehensive cross-domain analysis. We then present our findings across nine decision areas that emerged from our systematic review, demonstrating how ABMS addresses specific challenges in each area.

3.1. Previous literature reviews

ABMS in economic markets has been the subject of several comprehensive reviews over the past two decades, and each of them provides a unique perspective on the field's development. Early fundamental review by Tesfatsion and Judd (2006) represents a comprehensive collection focused on Agent-based Computational Economics (ACE) to establish it as a recognized field by providing practical guidance for newcomers, covering fundamental topics in the field and featuring essays from pioneering researchers. Their work characterized ACE as "the computational study of economic processes modeled as dynamic systems of interacting agents who do not necessarily possess perfect rationality and information", marking a departure from traditional equilibrium-based approaches. Following this foundation, Kirman (2010) provides a foundational critique of standard economic models while advocating for agent-based approaches. The book emphasizes that economic systems should be viewed as complex adaptive systems where agents constantly react to and influence each other. Kirman challenges the conventional notion that aggregate economic behavior can be understood through a "representative agent" approach. Instead, he argues that coordination rather than efficiency is the central problem in economics and that the direct interactions between individuals, firms, and banks form the basis of modern economic functioning. Later on, Gallegati et al. (2018) present a critical examination of conventional economic models while advocating for agent-based approaches, particularly in light of the 2008 financial crisis.

The field's evolution and maturation are evident in more recent comprehensive reviews. Chen et al. (2012) provided one of the first systematic reviews examining ACE models from an econometric analysis in financial markets perspective and established a framework for evaluating and comparing different modeling approaches. In another book, Chen (2017) presents a comprehensive scholarly examination of ACE, focusing on two fundamental questions: (1) what is ACE? and (2) to what extent is ACE useful or necessary for understanding economic processes? The book provides a meticulous academic treatment tailored for economists with strong analytical backgrounds and interest in empirically grounded economic modeling. In recent reviews, Arthur (2021) provides both a historical perspective and a systematic review of how agent-based approaches emerged and evolved within economics. Axtell and Farmer (2025) provide a comprehensive examination of ABMS application in economics and finance and trace its evolution from early implementations to current state-of-the-art applications across various fields over the past 60 years. Lastly, Tesfatsion (2023) present key modeling principles that characterize ACE, emphasizing its unique ability to study economic systems as open-ended, locally constructive sequential games. The authors distinguish ACE from traditional economic modeling approaches as it allows the investigation of rationality, optimality, and equilibrium conditions as testable hypotheses rather than imposed assumptions. These reviews collectively reveal the broad applicability of ABMS across different market contexts and highlight the need for a systematic categorization of applications by specific decision areas in market analysis. This categorization would not only help organize the existing literature but also identify gaps and opportunities for future research, particularly in addressing implementation challenges and integrating modern computational techniques.

The second stage of our systematic review, as presented in Section 1, is to identify influential papers in each of the nine distinct decision areas where ABMS has been effectively applied to analyze markets and decision-making processes in them. Table 1 presents an overview of paper selection criteria by providing details on decision area, search terms, number of initial articles, selection criteria, and selected papers. Our systematic review employs a consistent search methodology across all nine decision areas, with customized keywords for

Table 1. Paper selection process by decision area.

Decision Area	Search Terms	Scopus Results	Selected papers
Economic Forecasting and Market Dynamics	economic forecast*; market dynamic*; market equilibrium*; economic prediction*	37 papers	Poledna et al. (2023); Seppecher (2012); Schreinemachers and Berger (2011); Awwad and Ammoury (2019); Filatova, Van Der Veen, et al. (2009); Baindur and Viegas (2011); Fagiolo et al. (2004); Riddle et al. (2021); Filatova et al. (2011); BenDor et al. (2009)
Consumer Behavior	consumer decision*; purchase behavior*; consumer choice*; buying pattern*	71 papers	Sturley et al. (2018); Zhang and Zhang (2007); Schenk et al. (2007); Roozmand et al. (2011); De Haan et al. (2009); Dulam et al. (2021); Delcea et al. (2019); Liu et al. (2017); Scalco et al. (2019); N. Zhang and Zheng (2019); Giráldez-Cru et al. (2020); Sasaki et al. (2011)
Market Penetration	market entry*; market penetration*; product adoption*; product penetration*; product diffusion*	45 papers	Noori et al. (2016) Noori et al. (2016); Delre, Jager, Bijmolt, et al. (2007, 2016); Eppstein et al. (2011); Negahban et al. (2014); Nejad et al. (2015); Schramm et al. (2010); Shafiei et al. (2012); Amini et al. (2012)
Competition and Pricing Strategies	pricing; competitive behavi*; price compet*; price optimization	159 papers	(Algarvio & Lopes, 2022); Aliabadi et al. (2017); Aron et al. (2006); Awwad et al. (2015); Chang et al. (2016); Dehghanpour and Nehrir (2017); Dogan and Güner (2015); Filatova, Parker, et al. (2009); He, Wang, et al. (2013, 2016); Krause et al. (2006); Li and Shi (2012); Pan and Choi (2016); Poplavskaya et al. (2020); Van Der Veen et al. (2012); Rohitratana and Altmann (2012); Tellidou and Bakirtzis (2007); Yousefi et al. (2011); Zheng et al. (2012, 2016); He, Cheng, et al. (2013)
Financial Market Mechanisms and Stability	financial *stability, systemic risk; market microstructure; financial contagion; financial network*; interbank market*	43 papers	Aymanns and Farmer (2015) (Battiston et al., 2021); Bookstaber et al. (2018); Botta et al. (2021); Bottazzi et al. (2005); Cardaci (2018); Farmer et al. (2005); Grilli et al. (2014, 2015); Kluger and McBride (2011); Lamperti et al. (2019); Liu et al. (2020); Lussange et al. (2021); Poledna et al. (2014); Popoyan et al. (2017, 2020); Raberto et al. (2019); Riccetti et al. (2016, 2018); Safarzyńska and van den Bergh (2017); Samitas et al. (2018); Tedeschi et al. (2012); Vidal-Tomás and Alfarano (2020)
Policy Effects and Regulatory Impact	policy impact; regulatory impact; policy evaluat*; policy assess*; regulatory assess*; market regulation*	33 papers	Leombruni and Richiardi (2006); Bakam et al. (2012); Kashani et al. (2019); Kickhöfer et al. (2011); Klassert et al. (2015); Le Pira, Marcucci, Gatta, Inturri, et al. (2017); Moglia et al. (2018); Neugart (2008); Pearce and Slade (2018); Rai and Robinson (2015); Tian et al. (2016); Van Heeswijk et al. (2019); Vinogradov et al. (2020); Wu et al. (2018)
Innovation Diffusion and Market Diffusion	innovation diffusion; technology adoption; technology diffusion; innovation adoption; innovation spread; innovation process	89 papers	Bohlmann et al. (2010); Dawid et al. (2014); Delre, Jager, and Janssen (2007, 2010); Dubey et al. (2022); Kowalska-Pyzalska et al. (2014); Lengyel et al. (2020); Meles and Ryan (2022); Mohandes et al. (2019); Pakravan and MacCarty (2021); Palmer et al. (2015); Rai and Robinson (2015); Robinson and Rai (2015); Schwarz and Ernst (2009); Shi et al. (2020, 2021); Stavrakas et al. (2019); Stummer et al. (2015); Van Eck et al. (2011); Wolf et al. (2015)
Market Vulnerability and Crises	market vulnerabilit*; market crash; financial crisis; market collapse; banking crisis; market shock*	27 papers	Bookstaber et al. (2018); Dosi et al. (2015); Grilli et al. (2015); Klimek et al. (2015); Lamperti et al. (2019); Liu et al. (2020); Seppecher and Salle (2015); Lorscheid et al. (2019)
Market Impact and Volatility	market impact; price volatility; market volatility; price jump*; price fluctuation*; volatility cluster*; volatility dynamic*	47 papers	Alfarano et al. (2005); Chen et al. (2015); Cocco and Marchesi (2016); Cocco et al. (2017); Farmer et al. (2005); Jacob Leal et al. (2016); Leal and Napoletano (2019); Sun et al. (2014); Westphal and Sornette (2020); Wossen et al. (2018)

Note: This table summarizes the systematic literature review process across different decision areas. Search terms marked with asterisk (*) indicate wildcard searches.

each specific domain. We structured our Scopus search using the following template:

```
TITLE-ABS-KEY("agent-based*" OR "agent based*")
AND TITLE-ABS-KEY(econom* OR financ* OR market*)
AND TITLE-ABS-KEY([DECISION AREA-SPECIFIC KEYWORDS])
AND PUBYEAR > 2003
AND (LIMIT-TO(SRCTYPE",j"))
```

This template consists of several components:

- The first component ensures all results incorporate agent-based modeling approaches.
- The second component maintains focus on economic, financial, or market applications.
- The third component contains decision area-specific keywords that were customized for each of the nine identified domains.
- We limited results to journal articles published between 2004 and 2024 to provide a comprehensive 20-year retrospective of the field's modern development. This period was selected to capture the transition of ABMS into wider practical application, coinciding with significant advancements in computational capabilities and the publication of foundational works.

After conducting each search, we applied the following inclusion criteria to filter and select the most relevant papers: (1) presented original ABMS applications, (2) provided sufficient methodological detail and clear results or insights, and (3) were cited by other researchers in the field at least 20 times. This citation threshold was established to ensure the included studies have achieved a baseline level of community recognition, while remaining low enough to include high-quality, emerging research published in recent years (2020—2024) that may not yet have accrued high citation counts. We selected the representative papers for each area to ensure comprehensive but focused coverage. It is important to note that the volume of available literature varies significantly across decision areas (see Table 1). In broader categories such as "Consumer Behavior", initial search results often included studies from adjacent fields (e.g., engineering-focused energy consumption behavior) that lacked explicit market analysis components. These were filtered out during the refinement process. Consequently, the number of selected papers in each section reflects the underlying density of the relevant research field, with "Competition" and "Consumer Behavior" presenting a larger pool of applicable ABMS studies compared to specialized areas such as "Market Vulnerability" or "Volatility".

In the following sections, we review the papers in each of the ten key areas of ABMS application in market analysis.

3.2. Economic forecasting and market dynamics

We identified 11 articles that match our search criteria for economic forecasting and market dynamics. These research articles can be categorized into three interconnected groups. The research area of articles in the first group is "macro-level economic system modeling", including studies that ABMS is used for national economies, simulates decentralized matching across multiple markets, and analyzes the impacts of wage flexibility on macroeconomic stability. These macro-level models provide foundational frameworks that connect to more specific market applications. The second group of articles focuses on "market-specific dynamics within the broader economy", where they illustrate how ABMS can capture the complexities of specific markets while maintaining connections to broader economic outcomes. The last group of articles focuses on "natural resources and spatial economics", where authors explore how economic activities interact with space and natural resources.

3.2.1. Macro-level economic system modeling

Three identified studies are categorized in this group. Poledna et al. (2023) apply ABMS for macroeconomic forecasting by developing a comprehensive model that incorporates all economic sectors populated with millions of heterogeneous agents. Their model incorporated historical micro and macro data to simulate the Austrian economy. The authors demonstrated how ABMS can be used for economic forecasting and studying monetary policy effects and fiscal responses. In the second research, Riccetti et al. (2015) develop an agent-based model where agents (firms, households, and banks) interact via decentralized matching processes across four markets (goods, labor, credit, and deposit) to analyze intersections between financial and real economic factors. Their model addresses decision areas related to credit allocation, employment, consumption, and financial stability. The last article in this group applies ABMS to investigate wage dynamics and macroeconomic stability in a monetary economy where money creation and destruction result from interactions between heterogeneous agents (Seppecher, 2012). This study focuses on wage setting, pricing, and monetary policy decisions.

3.2.2. Market-specific dynamics within the broader economy

The research in this group demonstrates how ABMS can capture the complexities of specific markets while maintaining a connection to broader economic outcomes. For example, Awwad and Ammoury (2019) employed ABMS to analyze construction bidding processes where they modeled heterogeneous contractors with different risk profiles and behaviors. Their model simulates dynamic interactions among contractors competing for the projects, and it can capture the emergent bidding patterns from the interactions. In the second research, Riddle et al. (2021) apply ABMS to explore the consequences of different types of supply disruption in the rare earth elements market. Their model includes diverse market agents (mines, refiners, producers, and consumers) while modeling over 60 specific rare earth deposits with detailed data, and it demonstrates how disruptions ripple through supply chains and affect prices, production, and demand beyond the disruption period. Baindur and Viegas (2011) use ABMS to model competition in freight transport between regions by simulating the interactions between shippers and carriers while incorporating behavioral decision-making. Their model represents complex transport choice decisions at the company level and it enables capturing how policy interventions like subsidies and increased shipping frequency can affect the market share of participants. Lastly, Fagiolo et al. (2004) developed an evolutionary agent-based model of labor market dynamics, which explicitly models matching between firms and workers by including detailed job search, wage bargaining, and wage setting processes. Their simulations demonstrate how aggregate patterns emerge from complex micro-interactions, showcasing the value of disequilibrium approaches to labor markets.

3.2.3. Natural resources and spatial economics

The articles in this group demonstrate how ABMS can enhance our understanding of natural resource management and spatial economics by capturing heterogeneous decision-making, market interactions, and feedback loops between human activities and environmental systems at multiple spatial scales. BenDor et al. (2009) apply an agent-based dynamic model to fishery management to simulate how competition and cooperation influence economic and ecological sustainability. In this study, the authors model heterogeneous fisher agents that adapt their effort and allocation based on expected profits to harvest multiple fish species in order to simulate both competitive and cooperative decision rules. Filatova et al. (2009) present an agent-based model of land market that accounts for heterogeneity in the spatial landscape and among economic agents in the market to analyze the market.

3.3. Consumer behavior

This category encompasses 12 articles that demonstrate how ABMS captures the complexity of consumer decision-making processes and their market impacts. These studies represent a diverse application of agent-based approaches to model how consumers process information, form preferences, interact with their social environment, and ultimately drive market outcomes. We have organized these articles into four interconnected groups: Individual Decision-Making Processes, Social and Environmental Influences, Product-Specific Purchase Behavior, and Market-Level Impacts and Policy Implications.

3.3.1. Individual decision-making processes

This group of research examines the cognitive and psychological mechanisms driving consumer choices at the individual level. These articles model how internal factors such as personality traits and decision-making strategies affect purchasing behaviors and market outcomes. Roozmand et al. (2011) employ ABMS to model consumer decision-making based on cultural and personality factors. Their approach formulates the decision-making process of agents based on Hofstede's national culture model (Hofstede, 2001) and three traits of the Five-Factor model of personality (McAdams, 1992; McCrae & Costa, 1983) to simulate how these factors influence consumers' purchasing behavior. This application shows ABMS's capacity to capture heterogeneity in consumer behavior while connecting micro-level psychological processes to macro-level market outcomes. In another study, Zhang and Zhang (2007) use ABMS to study the decoy effect in consumer purchase decision-making. The authors develop a motivation function that integrates consumer psychological traits with market interactions to model how consumers make choices when facing competing brands. Their model explicitly represents factors like price sensitivity, quality sensitivity, susceptibility to advertising, and follower tendency. This research highlights ABMS's ability to reveal emergent market phenomena that arise from individual behavioral patterns and helps explain complex psychological aspects of consumer choice that traditional equilibrium models struggle to capture.

3.3.2. Social and environmental influences

This group of research explores how external factors such as social networks, peer influence, and information availability affect consumer choices. The articles in this group highlight the importance of social dynamics and environmental constraints in shaping consumer behavior. Sasaki et al. (2011) utilize ABMS to explore how the quantity of product information affects consumer decision-making. The authors first conducted human experiments in a simulated online shopping environment, then created an agent-based model to further investigate their findings. In this study, ABMS allowed the researchers to demonstrate how individual-level cognitive limitations can produce emergent group-level patterns of conformity. It also enabled them to control for agent preferences to measure how well those preferences were satisfied. Scalco et al. (2019) develop an agent-based model to simulate meat consumption behavior in Britain, with particular attention to how social influence across different networks affects dietary decisions. The model incorporates empirical data from British consumers to ground agent behavior in reality. The authors demonstrate how information spreads between contexts by explicitly modeling peer influence across multiple networks. For example, they were able to demonstrate how campaigns targeting workers at lunchtime could influence their household members' behavior at dinner. In the last study of this group, Delcea et al. (2019) employ ABMS to examine how consumer opinions about eco-friendly products spread through online social media environments. Their research focuses on how online interactions shape attitudes toward sustainable consumption. The authors incorporated survey data to simulate both individual preferences and social influence processes and characterized agents by variables including knowledge about eco-friendly products, environmental awareness, environmental attitudes, and susceptibility to social influence. Their simulations show that online media exposure significantly affected eco-friendly product adoption patterns.

3.3.3. Product-specific purchase behavior

This group focuses on how consumers make decisions about specific types of products or product attributes. These research analyze the complex interplay of factors that influence purchasing decisions for different product categories. De Haan et al. (2009) employ an agent-based microsimulation approach to model how consumers respond to financial incentives based on vehicle energy efficiency. The authors develop a detailed model where heterogeneous consumer agents choose from a highly granular set of vehicle options drawn from real-world car data. Their model demonstrates how financial incentives affect consumer purchases and provides insight that would be difficult to capture with traditional economic models. In another study, Liu et al. (2017) employ a hybrid simulation approach combining system dynamics and ABMS to investigate factors influencing consumers' willingness to pay for low-carbon products. The simulations in this study reveal that delivery speed and consumers' patience have the most significant effects on willingness to pay, while environmental awareness and income have surprisingly little impact. This research demonstrates ABMS's capability to uncover counterintuitive relationships between product attributes and consumer behavior while showing how factors beyond the obvious environmental considerations shape purchasing decisions for sustainable products. Lastly, N. Zhang and Zheng (2019) develop an agent-based model to simulate consumer purchase behavior based on three key product attributes: quality, price, and promotion. Their simulation demonstrates how consumers' purchase decisions emerge from the complex interplay of product attributes, while their model allows companies to test different attribute combinations to maximize market share.

3.3.4. Market-level impacts and policy implications

This group examines how individual consumer behaviors aggregate to create market-level effects and how policies can influence these outcomes. These articles demonstrate the ABMS's capacity to connect micro-level behaviors to macro-level market dynamics. Dulam et al. (2021) develop an agent-based model to simulate panic buying behavior during crises like the COVID-19 pandemic. They created a detailed multi-agent model combining consumer panic buying patterns with supply chain dynamics to quantitatively evaluate consumer panic purchase intentions while assessing impacts on supply chains throughout simulations. Giráldez-Cru et al. (2020) focus on creating more realistic representations of consumer perceptions by using fuzzy linguistic variables to model how consumers evaluate different aspects of products (e.g., price, quality, comfort) in their agent-based model. Their innovation is embedding 2-tuple fuzzy linguistic variables within consumer agents to better represent qualitative aspects of decision-making traditionally lost when converting to numerical values. The model demonstrates how individual preferences aggregate to influence market outcomes, showing no loss of information when applied to real market data. This approach provides a more natural representation of how consumers think about products, capturing the nuanced evaluation process that drives store and product choices. Schenk et al. (2007) present an agent-based model that simulates individual consumers in northern Sweden making shopping decisions based on store characteristics, personal preferences, and geographical factors. Their model captures how consumers evaluate aspects like price, quality, assortment, and distance when choosing stores and demonstrates that individual spatiotemporal behaviors aggregate to predict market shares with high accuracy. In another study with the same subject, Sturley et al. (2018) developed a proof-of-concept agent-based model that captures individual consumer behaviors around store choice, shopping frequency, mission, and spending patterns. The authors illustrate how ABMS can better capture evolving consumer behaviors (like increased convenience shopping and multi-purpose trips) that traditional spatial interaction models struggle to represent. They highlight the potential of ABMS to assess policy impacts on retail networks, especially for convenience formats and non-residential shopping.

3.4. Market penetration

Market penetration represents a critical strategic decision area for firms seeking to introduce new products or expand existing offerings into established markets. Our systematic literature review identified 10 articles that employ ABMS to study market penetration challenges. These studies explore how complex, adaptive market systems respond to various product introduction strategies and reveal patterns that emerge from interactions between heterogeneous market actors. The research in this decision area focuses primarily on understanding the dynamic processes through which products achieve market acceptance and diffusion. Unlike traditional analytical approaches that often rely on aggregate diffusion curves, ABMS studies of market penetration explicitly model individual decision-making entities and their interactions. We identified four interconnected approaches to studying market penetration through ABMS: strategic product introduction, supply-demand coordination, social influence dynamics, and external policy factors.

3.4.1. Strategic product introduction

The initial entry of products into markets can determine their long-term success or failure. This group represents research that examines how ABMS has been applied to understand and optimize strategic product introduction decisions. Amini et al. (2012) develop an agent-based model to analyze how different production-sales policies impact new product diffusion in supply-constrained environments. Their model captures the marketplace as a complex adaptive system where supply chain capacity is limited, consumers' adoption decisions are influenced by both marketing activities and word-of-mouth (both positive and negative), and consumer interactions occur in social networks at the individual level. Through over 1 million simulation experiments, they identify optimal production-sales policies for various conditions and find that a build-up policy with delayed marketing generally outperforms other approaches, especially when negative word-of-mouth effects are considered. Delre, Jager, Bijmolt, et al. (2007) employ ABMS to examine the effectiveness of different promotional strategies for new product launches while focusing on the targeting and timing of promotions. Their model simulates individual consumer decision-making within a social network, capturing how word-of-mouth and marketing efforts influence adoption. The last research in this group was done by Nejad et al. (2015), where the authors employ ABMS to investigate how consumer homophily (the similarity between connected consumers in a social network) affects the success of product seeding programs. In this study, ABMS enables the incorporation of empirical social network structures and homophily patterns among consumers, which allows authors to observe how individual-level similarity between connected consumers affects macro-level market outcomes through network effects that would be impossible to study through controlled experiments in real markets.

3.4.2. Supply and demand coordination

Achieving successful market penetration requires careful coordination between supply capabilities and evolving market demand. ABMS makes it possible to simulate individual consumer adoption decisions alongside manufacturer production planning and investigate how supply constraints can bottleneck diffusion processes, and conversely, how excess production capacity can lead to inefficient resource allocation. For example, , Amini et al. (2012,), model presented in the first group can be used to analyze alternative supply chain production-sales policies for new product diffusion. Negahban et al. (2014) develop an agent-based model to analyze different production planning strategies for managing new product diffusion under various levels of volume flexibility and consumer social network structures. Their model features a manufacturing firm that can adjust production levels based on demand forecasts, which creates a dynamic interaction between production capabilities and market uptake. In another study, Shafiei et al. (2012) employ ABMS to predict the evolution of the Electric Vehicle (EV) market share in Iceland. Their model accounts for internal combustion engine vehicles currently dominating the market alongside EVs expected to enter the market in the future. In their model, vehicles compete for market penetration through a choice algorithm incorporating social influences and consumer preferences for vehicle attributes.

3.4.3. Social influence and network dynamics

Social interactions and network structures play a fundamental role in market penetration processes, as consumers rarely make adoption decisions in isolation. The following articles explore how ABMS has been used to capture and analyze the critical role of social influence in driving market penetration. These models explicitly represent consumers as interconnected agents whose decisions are influenced by their social contacts, allowing researchers to examine how network topology, interaction dynamics, and consumer heterogeneity shape adoption patterns. For example, Delre et al. (2016) develop an agent-based model that simulates the U.S. motion picture market where consumer agents make decisions based on internal influences (word-of-mouth), external influences (advertising), and shared consumption (watching movies together). This application effectively captures how social dynamics combine with marketing efforts to create complex diffusion patterns in entertainment markets. In another study, Eppstein et al. (2011) design and implement a spatially explicit agent-based consumer choice model for plug-in hybrid electric vehicle adoption that accounts for social influences and media impact among heterogeneous consumer agents. In this study, the simulations capture how social influence creates neighborhood clustering of adoption patterns. Lastly, Schramm et al. (2010) diffusion model incorporates both consumer and brand agents in the digital camera market, modeling brand-level and product-category diffusion simultaneously. Their model defines consumer agents by innovativeness and sensitivity to product features, price, and promotion, while incorporating market entry timing and brand characteristics to simulate competitive dynamics. This research demonstrates how brand-level diffusion curves aggregate to form product-category diffusion patterns and reveals emergent competitive dynamics that would be difficult to capture with traditional diffusion models.

3.4.4. Policy and external influence

Policies and external influences, such as socioeconomic factors, can significantly accelerate or impede the market penetration of a product. The research in this group employ ABMS to understand the role of such external influences in shaping market penetration outcomes. For instance, Noori and Tatari (2016) develop an agent-based model to predict regional EV market shares where the model accounts for consumer preferences across vehicle attributes (purchase prices, maintenance costs, environmental damage costs, and water footprint) with specific attention to 22 different electricity grid regions in the United States. In this study, the authors also examined the effects of government subsidies and word-of-mouth on market shares, and the simulation results demonstrated the importance of targeted policies. In an extension of previous models, Noori et al. (2016) extend their analysis to predict EV market penetration rates while considering uncertainties such as regulation service payments, signal features, and battery degradation across different regions.

3.5. Competition and pricing strategies

ABMS has been applied for modeling competition and pricing strategies across various markets. Throughout our systematic literature review, we identified 21 articles in this decision area that highlight ABMS's significant contribution to understanding how firms compete and set prices in complex market environments. The research in this category demonstrates how agent-based approaches can capture the dynamic, adaptive nature of pricing decisions and competitive behaviors that traditional equilibrium models often struggle to represent. These articles collectively examine how market participants develop bidding strategies, respond to competitors, adapt to changing market conditions, and optimize pricing decisions in the face of heterogeneous consumer preferences and varying market structures. We have organized these studies into three distinct groups, each representing an interconnected methodological approach: Learning-Based Strategic Behavior, Market Mechanisms and Structural Dynamics, and Consumer-Environment Interactions and Pricing. Each category represents a different perspective on how ABMS can simulate competitive dynamics and pricing strategies, from the micro-level learning processes of individual market participants to the macro-level impacts of market design and consumer behavior.

3.5.1. Learning-based strategic behavior

The initial development and evolution of pricing strategies represent a phase that can determine market outcomes and competitive positioning. This group of research uses ABMS to understand how market participants learn, adapt, and refine their competitive strategies through experience. There are multiple research using ABMS to study electricity market dynamics. Krause et al. (2006) compare Nash equilibria analysis with ABMS for assessing electricity market dynamics while using reinforcement learning to model generator bidding behavior. The authors demonstrate how agent-based models can reveal important market dynamics, particularly in scenarios with multiple Nash equilibria where generators learn to cycle between different strategies. Li and Shi (2012) employ ABMS to investigate bidding optimization for wind generators in deregulated electricity markets. In their model, generation companies are modeled as adaptive agents using reinforcement learning algorithms to improve their bidding strategies. In another study, Tellidou and Bakirtzis (2007) employ agent-based simulation to study capacity withholding and tacit collusion in electricity markets, modeling generators as adaptive agents using a simulated annealing Q-learning algorithm. The authors demonstrate how tacit collusion can emerge through repeated market interactions even under competitive conditions without explicit communication. Yousefi et al. (2011) introduce a composite demand function and comprehensive demand response model within an agent-based retail electricity market to determine optimal real-time pricing. In this model, the retail energy provider is an intelligent agent using Q-learning to discover profit-maximizing pricing strategies while considering customer response.

Some studies in this group target the supply chain. For example, He, Wang, et al. (2013) utilize ABMS to study retailer competition and evolution in multi-product supply chains. The authors develop an agent-based retail model with three types of agents (suppliers, retailers, consumers) whose optimal behaviors are determined through a genetic algorithm. Lastly, He, Cheng, et al. (2013) employ ABMS to investigate the optimal location and pricing strategies for intermediaries in hierarchical distribution systems. The authors develop a spatial agent-based model with four agent types (world, manufacturer, firms, consumers) and use genetic algorithms to derive firms' optimal evolutionary pricing and locating strategies.

3.5.2. Market mechanisms and structural dynamics

Achieving successful market outcomes requires carefully designed market structures that align individual incentives with the efficient allocation of resources. The papers in this group employ ABMS to examine how different market designs, pricing rules, and institutional arrangements affect participant behavior and market performance. Algarvio and Lopes (2022) develop an agent-based model of the electricity retail market to assist retailers in optimizing their consumer portfolios. Their model is inspired by financial market models where they treated consumers as assets in the financial market, and retailer agents with different risk preferences compete to sign contracts with real-world consumers. Aliabadi et al. (2017) employ ABMS to investigate how different electricity market-clearing mechanisms affect power generation companies' strategic behavior. In this research, the authors develop a model that integrates game theory with reinforcement learning to simulate generators' bidding strategies regarding multiple pricing rules and rotating policies. Poplavskaya et al. (2020) use ABMS to analyze how regulatory changes in the European electricity balancing market affect strategic bidding in this market. In their model of the market, the authors implement agents with different strategies to examine how different market designs affect the bidding behavior and economic efficiency. Van Der Veen et al. (2012) utilize ABMS to analyze how alternative imbalance pricing mechanisms influence balancing market performance. In their study, they develop a model where Balance Responsible Parties (BRPs) (Organizations responsible for matching their customers' actual electricity production/consumption with what they scheduled in advance) make autonomous decisions about their balancing strategies. The model simulates how these BRP agents learn from past results, adjusting their strategies of intentionally over- or under-contracting energy to minimize their imbalance costs. Dehghanpour and Nehrir (2017) employ ABMS to create a hierarchical bargaining framework for power management across multiple cooperating microgrids. The authors model microgrid and utility company agents that interact through a distributed optimization approach using Nash Bargaining solution, which allows them to negotiate fair and Pareto-optimal outcomes without a central controller. Rohitratana and Altmann (2012) develop an agent-based model to investigate how different pricing schemes affect software markets offering both Software-as-a-Service and perpetual software licenses. Their model features vendor agents implementing various pricing strategies and customer agents making decisions using an specific process. The last research in this group was done by He, Cheng, et al. (2013), where the authors present a spatial agent-based model to study competitive hierarchical distribution systems, modeling four types of agents (world, manufacturer, firms, and consumers) to analyze optimal location and pricing strategies. The authors employ genetic algorithms to help agents evolve optimal behavioral strategies and enable the emergence of complex system dynamics that would be impossible to capture with traditional operations research methods.

3.5.3. Consumer-environment interactions and pricing

Consumer behavior and environmental constraints play a fundamental role in shaping pricing strategies, as market participants rarely make decisions in isolation. The research in this group employs ABMS to capture and analyze the role of these factors in driving pricing dynamics. Aron et al. (2006) use ABMS to model electronic markets where agents can evaluate buyers, customize products, and price in real-time operation. Their model can capture how intelligent pricing agents and customers interact in customization scenarios where ABMS enables them to represent both individual decision-making behaviors and their aggregate market effects when dealing with information goods. Awwad et al. (2015) develop an agent-based model to study competitive construction bidding processes by simulating contractors with different risk attitudes, cost estimation skills, and project management capabilities. Chang et al. (2016) employ ABMS to model pricing strategies for perishable agricultural products. The model has been used in simulation experiments to demonstrate how different proportions of customer preferences affect optimal pricing strategies, where there are six retailers with different pricing strategies and hundreds of customers with diverse preferences. Filatova, Parker, et al. (2009) develop a bilateral agent-based land market model where buyers and sellers negotiate on price and due dates with explicit behavioral drivers. In this study, the authors use ABMS to capture micro-level interactions between heterogeneous agents in land markets and show how the relative market power between buyers and sellers affects urban morphology and land rent patterns. Pan and Choi (2016) employ ABMS to model a two-phase negotiation process in fashion supply chains where manufacturers and suppliers are cooperative on delivery dates but competitive on prices. In this research, the agent-based approach enables capturing the complex interdependencies and behavioral adaptations in supply chain negotiations, with intelligent algorithms (simulated annealing) helping agents search for optimal agreements. Zheng et al. (2012) combine a macroscopic traffic congestion model with an agent-based simulator to develop a dynamic cordon pricing scheme for urban road networks. Their model can capture travelers' heterogeneous choices and behaviors in response to congestion pricing, revealing how pricing affects different trip purposes differently. Lastly, Zheng et al. (2016) develop a time-dependent area-based pricing scheme for multimodal urban networks with heterogeneous users where they employ ABMS to model travelers with different values-of-time. This approach allows them to investigate equity impacts across user groups and evaluate incentive programs encouraging public transport use.

3.6. Financial market mechanisms and stability

ABMS can assist in understanding the complex dynamics of financial markets and their stability by modeling them from bottom up and revealing how macro-level patterns and systemic behaviors emerge from interactions between diverse market participants. We identified 23 studies that fit our search criteria for this category and based on their content, we categorize them into six distinct groups that better reflect their application within this category of research: Financial network structure and contagion mechanisms, Market microstructure and price formation, Leverage cycles and financial instability, Financial regulation and macroprudential policy, Inequality, financialization and market dynamics, and Cross-sectoral risks and sustainability challenges. Furthermore, we present each of these groups and briefly outline the research perspective of the articles within each group.

3.6.1. Financial network structures and contagion mechanisms

Financial markets function as complex networks of interconnected institutions, which makes it important to understand their structures for assessing the systemic risk of these markets. The research in this group employs ABMS to model how network topology influences contagion dynamics, revealing non-intuitive relationships between connectivity and stability. These models capture how financial linkages can facilitate both risk sharing during normal times and the rapid propagation of shocks during crisis periods, providing crucial insights into the modern financial systems. Tedeschi et al. (2012) research employs ABMS to model a three-sector economy focusing on how the interbank market propagates bankruptcy cascades through networks with varying connectivity patterns. Their model includes heterogeneous firms and banks with random connectivity, capturing how network structure fundamentally affects cascade dynamics and severity. Bookstaber et al. (2018) present an agent-based model of financial network structures by creating a comprehensive system with three agent types: cash providers (such as money market funds), banks/dealers, and hedge funds. Their model endogenously generates network connections through agent interactions, demonstrating how the reaction to initial losses, rather than the losses themselves, determines the extent of a crisis. Grilli et al. (2014) use ABMS to model a three-sector economy representing goods, credit, and the interbank market with 1000 firms and 50 banks. Their research demonstrates how interbank linkages allow banks to share credit risk, but at the same time, they can spread one bank's crisis through the whole network. In another study, Grilli et al. (2015) research employs ABMS to focus on how network connectivity affects contagion patterns. This model simulates agent heterogeneity in size and behavior while capturing how excessive connectivity creates severe trade-offs between risk diversification benefits and heightened systemic risk. In this study, ABMS reveals a "pseudo-optimal" connectivity level and demonstrates that complete networks are not necessarily more stable than sparse ones. Liu et al. (2020) develop a comprehensive agent-based model representing all 6600 U.S. banks at 1:1 scale, focusing on endogenous network formation through individual bank decision-making based on balance sheet ratios and relationship scores. The model incorporates overnight, short-term, and long-term lending relationships with dynamic formation and dissolution, demonstrating how endogenous choices are necessary for understanding loss development as networks evolve. The ABMS approach in this research demonstrates that endogenous network formation offers greater system resilience compared to static networks, as banks adaptively adjust their relationships during periods of stress.

3.6.2. Market microstructure and price formation

In financial markets, the fundamental processes of price discovery and market functioning arise from the interactions between diverse market participants who are operating under specific trading protocols. Research in this category utilizes ABMS to investigate how various market microstructures and agent behaviors generate emergent price dynamics, volatility patterns, and liquidity conditions. These models illustrate how institutional arrangements and behavioral factors influence market outcomes, providing insights into the conditions that foster efficient price formation or contribute to market instability. Bottazzi et al. (2005) demonstrate how ABMS can examine the interaction between different trading protocols and heterogeneous agent behaviors in financial markets. The authors model agents with varying behavioral types to investigate how institutional arrangements shape market dynamics independently of strategic agent behavior. Their simulations reveal that market microstructure features (such as skewness, kurtosis, and autocorrelation patterns) are largely determined by trading mechanisms rather than agent rationality, with different protocols generating distinct statistical properties even when agent populations remain constant. Farmer et al. (2005) employ ABMS with minimal agent intelligence to demonstrate how market institutions can dominate strategic behavior in price formation processes. The authors model "zero-intelligence" agents who place orders randomly subject to budget constraints within a continuous double auction framework, testing simple quantitative laws relating order-arrival rates to market properties like spreads and price diffusion. Their model successfully predicts spread variance and price diffusion variance across 11 London Stock Exchange stocks, showing that institutional constraints and order flow mechanics can generate realistic market microstructure patterns without requiring sophisticated agent strategies. Kluger and McBride (2011) use ABMS to explore how asymmetric information between informed and uninformed agents generates concentrated intraday trading patterns through learning mechanisms. The authors model agents who learn when to trade using genetic algorithms and reinforcement learning, while implementing zero-intelligence behavior for all other trading decisions within a double auction framework. Their simulations demonstrate that uninformed liquidity-motivated agents can coordinate to avoid adverse selection losses by concentrating trades at market opening while reproducing empirically observed U-shaped intraday volume patterns without requiring full rationality or strategic equilibrium concepts. Lussange et al. (2021) advance ABMS by incorporating sophisticated reinforcement learning algorithms where each agent autonomously learns both price forecasting and trading strategies while balancing chartist and fundamentalist approaches. The authors model agents using two distinct reinforcement learning algorithms within a centralized order book system, calibrating the model to London Stock Exchange data from 2007–2018. Their approach successfully reproduces key market microstructure statistics including return distributions, volatility clustering, and autocorrelation patterns, demonstrating that agent learning processes can generate realistic emergent market dynamics as an emergent property of the multi-agent system. Lastly, Vidal-Tomás and Alfarano (2020) employ the Kirman herding model (Kirman, 1993) to describe the evolution of investor sentiment through the collective movement of stock prices across multiple global markets. Their agent-based approach models how individual stocks transition between optimistic and pessimistic states, based on both idiosyncratic shocks and global coupling effects. The collective behavior emerges from social interactions and herding phenomena among traders. Their model successfully captures key market microstructure features, such as heteroskedastic volatility clustering, fat-tailed return distributions, and exponential autocorrelation patterns, while enabling the development of an early warning indicator that can predict market turning points by detecting asymmetries in investor sentiment across different market phases.

3.6.3. Leverage cycles and financial instability

Credit dynamics and leverage cycles represent core mechanisms that shape financial instability and propagation through economic systems. The studies in this group apply ABMS to model how debt accumulation, collateral constraints, and feedback loops between asset prices and balance sheets create endogenous boom-bust cycles. The models presented in these studies demonstrate how rational behaviors at the micro level can generate unsustainable leverage patterns and eventual systemic crises while providing a rich framework for understanding financial fragility. Aymanns and Farmer (2015) employ ABMS to model leveraged investors (banks) that adjust their leverage based on Value-at-Risk constraints using historical asset price observations, creating a feedback loop where low perceived risk leads to high leverage and vice versa. Their simplified agent-based framework demonstrates how pro-cyclical leverage management leads to endogenous irregular oscillations characterized by gradual price increases followed by drastic market collapses, illustrating the emergence of leverage cycles from individual risk management decisions. The model illustrates how countercyclical leverage policies can stabilize the system by breaking destabilizing feedback loops, offering insights for macroprudential regulation to manage systemic risk. Botta et al. (2021) develop a hybrid agent-based macroeconomic model featuring heterogeneous households and aggregate sectors. In this model, securitization and collateralized debt obligations emerge endogenously to satisfy wealthy households' demand for high-return assets. Their model captures how increasing inequality drives demand for complex financial products while simultaneously enabling commercial banks to extend more loans through securitization, creating a self-reinforcing cycle where interest payments from indebted households become income streams for wealthy rentiers. The simulations demonstrate how this inequality-driven financialization process leads to higher economic growth in the short run but comes at the cost of increased financial instability and deeper economic crises in the long term. Cardaci (2018) employs the ABMS model to simulate a credit-network economy with heterogeneous households and banks. This model incorporates peer effects in consumption through expenditure cascades and home equity extraction mechanisms driven by house price appreciation. The model simulates how rising income inequality triggers upward-looking consumption behavior among lower-income households, who use collateralized loans and mortgages to maintain consumption levels, creating a debt-financed consumption boom that temporarily sustains economic growth. Riccetti et al. (2016) develop an agent-based macroeconomic model with heterogeneous households, firms, and banks interacting in credit, labor, goods, and deposit markets, where they systematically vary dividend payout policies to simulate the shift from one financialization strategic characteristic to another. Their model demonstrates how increasing dividend distributions create a nonlinear relationship with financial stability, as reduced retained earnings weaken firm and bank balance sheets while increasing leverage requirements. The simulations reveal how financialization through payout policies creates a temporary wealth effect that supports consumption in the short run, but ultimately leads to credit rationing and higher unemployment as financial fragility accumulates. This result showcases the trade-offs between short-term growth and long-term stability.

3.6.4. Financial regulation and macroprudential policy

Creating effective financial regulation requires understanding how market participants adapt to changing rules and constraints. Research in this domain employs ABMS to evaluate regulatory approaches by modeling how diverse agents respond to policy interventions. These studies frequently uncover unexpected consequences of seemingly straightforward regulations and highlight where collective adaptations might undermine policy intentions Poledna et al. (2014) employ ABMS to analyze leverage-induced systemic risk under credit risk policies. They model value investors, noise traders, and banks to examine how different regulatory schemes affect market stability and default rates. Their model captures how regulatory policies can paradoxically increase systemic risk by forcing synchronized selling during deleveraging periods, revealing that none of their research subjects' credit risk policies are optimal for all market participants. Popoyan et al. (2017) develop an agent-based model to study interactions between monetary and macro-prudential policies. The simulation involves heterogeneous firms, workers, and banks operating under different regulatory frameworks. The research demonstrates how ABMS can identify optimal policy combinations by capturing emergent properties from complex agent interactions that traditional models may overlook. In another study, Popoyan et al. (2020) extend their framework to include interbank markets and model how financial instability emerges from the co-evolution of interbank and credit markets under different regulatory and monetary policy scenarios. Their model showcases how ABMS can be utilized to design and test novel regulatory instruments by simulating their effects on complex financial networks prior to real-world implementation. Lastly, Riccetti et al. (2018) employ ABMS to explore the effects of banking regulation on financial stability by creating a decentralized matching macroeconomic model populated by heterogeneous agents (households, firms, and banks) that interact directly across multiple markets (goods, labor, credit, and deposits). Their model demonstrates ABMS's capacity to evaluate regulatory approaches by simulating how diverse banking agents respond to different policy interventions, specifically examining minimum capital requirements and lending concentration limits while incorporating dynamic payout policies. The simulations reveal complex, nonlinear relationships between regulatory tightness and macroeconomic outcomes.

3.6.5. Inequality, financialization and market dynamics

The distribution of wealth and income has a deep impact on financial markets and economic stability. Studies in this group utilize ABMS to examine the interaction between economic inequality and financial innovation, as well as the impact of credit expansion. Botta et al. (2021) employ a hybrid agent-based model featuring heterogeneous households and aggregate financial sectors to examine how income inequality co-evolves with modern financial systems. Their model captures the relationship between rising inequality and financial innovation. The model illustrates how credit expansion initially boosts economic growth but can ultimately lead to financial crises. This research highlights ABMS's capacity to reveal the complex feedback loops between distributive dynamics and the evolution of financial markets Cardaci (2018) develops an agent-based macroeconomic model with heterogeneous households and banks to investigate how rising income inequality drives household debt accumulation through peer effects and home equity extraction mechanisms. The model incorporates expenditure cascades combined with a housing market that captures the behavioral and institutional factors behind the 2007–2008 financial crisis. The study by Riccetti et al. (2016), which was mentioned earlier in the leverage cycles and financial instability group, can also be categorized in this group, as the authors use ABMS to analyze how dividend distribution policies by firms and banks affect financial stability and macroeconomic dynamics.

3.6.6. Cross-sectoral risks and sustainability challenges

Financial markets exist within broader ecological, social, and political contexts that increasingly influence their stability. Articles in this group apply ABMS to analyze how external developments propagate through financial networks. These models map the transmission mechanisms that link non-financial disruptions to financial instability, helping to identify previously overlooked vulnerabilities. Battiston et al. (2021) demonstrate how ABMS can model the transmission of climate risks through financial networks by representing heterogeneous agents (banks, firms, and households) with different exposures to climate-related shocks. Their model captures how physical climate damages propagate through interconnected financial institutions, creating cascading effects that can amplify systemic risk. This research highlights how ABMS can quantify the hidden costs of climate-induced financial instability that traditional equilibrium models might miss. Lamperti et al. (2019) employ a global agent-based integrated assessment model to examine how climate damages affecting labor and capital productivity create financial system vulnerabilities through firm bankruptcies and non-performing loans. Their model includes heterogeneous households, firms, energy plants, and banks, simulating how climate shocks propagate through credit networks and create feedback loops between the real economy and financial sector. Their simulation results demonstrate how ABMS can capture the complex, non-linear relationships between environmental pressures and financial stability. Raberto et al. (2019) use the Eurace agent-based macroeconomic model (Cincotti et al., 2010) to investigate how differentiated banking capital requirements can redirect credit flows from speculative activities toward green investments in renewable energy technologies. The model simulates interactions between banks, firms, households, and regulators, incorporating heterogeneous capital goods with varying energy efficiency levels to examine how financial policies can promote sustainability transitions. Their research exemplifies how ABMS can evaluate the complex dynamics of sustainable finance policies. Safarzyńska and van den Bergh (2017) develop an agent-based model that integrates technological evolution, interbank markets, and electricity sectors to analyze how rapid investments in renewable energy affect financial stability through changes in interbank connectivity. Their model includes heterogeneous consumers, producers, power plants, and banks, simulating how energy transition policies alter credit flows and network structures in ways that can either enhance or undermine the resilience of the financial system. The research showcases how ABMS can capture unintended consequences of sustainability policies across interconnected systems. Lastly, Samitas et al. (2018) employ an object-oriented agent-based simulation to model how political events like Brexit create cross-border financial disruptions by suddenly fragmenting previously integrated economic networks. Their model represents banks, firms, households, and regulators in both UK and EU economies to simulate how the separation affects trade flows, capital allocation, and banking relationships across jurisdictions. Their simulations reveal that Brexit imposes significant long-term costs on both sides, with particularly severe impacts on EU financial stability, demonstrating how ABMS can assess the systemic risks of major political and economic transitions that traditional models struggle to capture.

3.7. Policy effect and regulatory impact

Policy interventions often involve multiple stakeholders with heterogeneous preferences and generate cascading effects across interconnected systems. These properties make traditional analytical approaches insufficient for comprehensive policy evaluation. ABMS addresses these challenges by enabling researchers and policymakers to model the dynamic interactions between individual agents, institutional frameworks, and market mechanisms, providing insights into both intended and unintended consequences of policy interventions. In a literature review, Kremmydas et al. (2018) conduct a systematic review of empirical agent-based models for agricultural policy evaluation and examine model transparency, agent behavior modeling approaches, and population synthesis methods. The applications of ABMS in analyzing policy effects and regulatory impact can be categorized into the following four areas that span the entire policy lifecycle, from initial design and optimization through implementation impact assessment to long-term systemic transformation. Each of these groups addresses different analytical needs and temporal perspectives, while together they demonstrate how ABMS provides a complete framework for understanding the multi-faceted nature of policy interventions in complex economic systems.

3.7.1. Policy design and predictive evaluation

This group encompasses studies that use ABMS to design optimal policy configurations and predict future outcomes under different policy scenarios. Bakam et al. (2012) employ ABMS to evaluate the cost-effectiveness of different greenhouse gas mitigation policies in Scottish agriculture. The authors model heterogeneous farmers with varying farm structures, costs, and abatement potentials who make economically rational decisions about adopting mitigation measures. Their model simulates how farmers respond to three policy instruments while incorporating transaction costs that are typically overlooked in policy evaluations. The model demonstrates ABMS's capability to predict policy outcomes under different scenarios. Pearce and Slade (2018) develop an ABMS to evaluate feed-in tariff policies for solar photovoltaic (PV) adoption in Great Britain. They model heterogeneous households as agents with diverse characteristics (income, social networks, and electricity consumption) who make adoption decisions based on multi-criteria utility functions that incorporate payback periods and capital costs. This research showcases ABMS's predictive capabilities of various cost and policy scenarios. Van Heeswijk et al. (2019) apply ABMS to evaluate the sustainability of urban consolidation centers in Copenhagen by modeling multiple agent types with distinct objectives and decision-making processes operating across strategic, tactical, and operational time horizons. Their comprehensive simulation framework tests 1458 different policy schemes, combining administrative measures and cost settings, and demonstrates significant environmental benefits while identifying the critical challenge of financial sustainability. This study demonstrates ABMS's capacity to inform the design of complex, multi-stakeholder policies. Wu et al. (2018) employ ABMS to investigate low carbon transitions in distributed energy systems. The authors model the competition between high and low carbon energies through agent behavioral rules that capture local dynamics of energy production and consumption under market fluctuations. Their simulation incorporates feedback mechanisms between energy supply and demand within localized markets, with industrial firms making economically rational decisions about energy purchasing while energy development rates adapt to demand patterns. The research demonstrates ABMS's capability to identify optimal policy configurations through acomprehensive analysis of the parameter space.

3.7.2. Policy impact assessment and distributional analysis

Policy interventions rarely affect all population segments equally, yet traditional evaluation methods often overlook these distributional consequences. Papers in this group utilize ABMS to reveal how policies create winners and losers across different income groups, geographic regions, and demographic categories. These models demonstrate that policies may achieve aggregate positive outcomes while simultaneously creating displacement effects or exacerbating inequalities, highlighting the importance of considering heterogeneous impacts in policy evaluation. . Kickhöfer et al. (2011) employ ABMS in their research to evaluate transport policies by modeling heterogeneous household agents across different districts in Greater Amman. Their model simulates individual travel decisions to capture how households choose between different transportation modes based on cost and availability constraints. The ABMS reveals how changes in transport policy create distinct winners and losers across income groups and geographic areas. Klassert et al. (2015) develop an agent-based model featuring agents representing different districts, income classes, and water supply conditions in Amman. In their model, agents make decisions about water consumption from multiple sources based on intermittent supply schedules and pricing policies. Their model demonstrates how water demand management policies create heterogeneous effects across districts and income groups, revealing that policies affecting tanker water supply disproportionately burden households in areas with high supply intermittency. Meanwhile, the simulation results show that tariff changes can create unexpected geographic patterns of winners and losers, even within the same income class. Leombruni and Richiardi (2006) implement a comprehensive agent-based model with 50,000 individual agents representing the Italian population. In their model, each agent makes lifecycle decisions about education, labor force participation, and retirement based on cohort-specific behavioral rules and changing policy environments. The model integrates multiple modules to simulate how pension reforms, educational trends, and changes in participation behavior affect different demographic groups over time. In this research, ABMS reveals how recent pension reforms will create differential impacts across gender, education, and age cohorts. Lastly, Neugart (2008) develops an agent-based model to investigate the investment decisions of individuals using reinforcement learning while the government provides training subsidies financed through taxation of employed workers. The model simulates how training policies affect job matching by allowing workers to invest in skills that qualify them for jobs in different sectors, creating competition between subsidized and non-subsidized job seekers. The ABMS reveals a crucial policy displacement effect where government training subsidies improve employment outcomes for beneficiaries at the direct expense of non-beneficiaries.

3.7.3. Stakeholder behavior and policy acceptance

Besides the importance of policy design quality, stakeholder acceptance and behavioral responses, which are influenced by social interactions and community attitudes, are also indicators of policy success. Studies in this groups show how ABMS captures the social dynamics that determine policy adoption, revealing that the same policy can succeed or fail depending on the social context and network effects. In this topic, Kashani et al. (2019) develop an agent-based model to evaluate building owners' response to promotion policies. The authors integrate heterogeneous preferences and social interactions among owners through a relative agreement model that characterizes how agent interactions influence their beliefs and decisions in their model. This model illustrates how social interactions can either amplify or mitigate the impact of policies, depending on community attitudes. Le Pira, Marcucci, Gatta, Inturri, et al. (2017) integrate discrete choice models with agent-based models to evaluate stakeholder policy acceptability in urban freight transport while modeling heterogeneous stakeholders with individual utility functions derived from stated preference surveys. Their approach simulates participatory decision-making processes in which stakeholders interact through opinion dynamics mechanisms to identify shared policy packages while taking into account both individual preferences and consensus-building dynamics. In another study, Le Pira, Marcucci, Gatta, Ignaccolo, et al. (2017) propose a comprehensive decision-support procedure that combines discrete choice models with ABMS to support stakeholder involvement in urban freight transport policy-making, representing multiple agent types with distinct behavioral rules and interaction patterns. Their integrated modeling approach enables evaluation of policy acceptability by simulating how stakeholder preferences and social dynamics influence collective decision-making outcomes. Moglia et al. (2018) develop a model to analyze the adoption of energy-efficient technologies and specifically solar hot water systems by residential customers. In their model, they incorporate financial and non-financial factors for household decision-making. Their simulations demonstrate that policy success depends not only on economic incentives but also on social timing and trusted information sources. The results of this research indicate that understanding "who influences whom and when" is crucial for policy design, meaning that the same rebate amount can succeed or fail based on whether it is delivered through trusted social channels at the right time. Lastly, Rai and Robinson (2015) implemented an agent-based model of residential solar PV adoption using multiple data sources, including surveys, utility programs, and geographic data. In their model, agents make decisions based on both attitudinal and control (affordability) components that evolve through social interactions. This research illustrates how social network effects can either amplify or dampen the impact of policy interventions over time. The study emphasizes the importance of policy timing by demonstrating that the same economic incentive can be ineffective early in adoption but highly effective later, purely due to social network effects and peer influence.

3.7.4. Regulatory framework analysis and market dynamics

Regulatory interventions create dynamic feedback loops with market forces that can lead to unexpected outcomes and system instabilities. Research in this area utilizes ABMS to examine how regulations shape market behavior and how market responses can, in turn, either undermine or enhance regulatory effectiveness. Vinogradov et al. (2020) demonstrate how ABMS can effectively model the complex interactions between housing market regulations and tourism-induced market dynamics. The authors employed agent-based modeling to investigate how different regulatory interventions affect Airbnb's growth patterns and their impact on local rental housing markets, using Norwegian Airbnb listings data for empirical validation. Their model incorporates imperfect rationality and exogenous factors by adding elements of randomness and probability to prevent instantaneous, perfectly calculated decisions. The study showcases how ABMS can capture the complex feedback loops between regulatory interventions and market responses, where the authors conclude that agent-based models using real-world data for individual cities may be valuable tools for choosing optimal practical regulatory solutions in each case.

3.8. Innovation and market diffusion

Diffusion is defined as the process by which an innovation is adopted through certain channels over time among the members of a social system (Rogers et al., 2014). Innovation and market diffusion modeling seeks to understand and predict how new products, technologies, or ideas spread through a market over time. Agent-based models in this domain capture the complex interplay of individual decision-making, social influences, and market dynamics that drive adoption processes. These models can simulate heterogeneous consumer behaviors, network effects, and the impact of marketing strategies or policy interventions.

Several comprehensive reviews have examined the state of ABMS in innovation diffusion. Kiesling et al. (2012) provide an overview of both theoretical and empirical models, highlighting this modeling approach's strengths in capturing heterogeneity and social interactions. The authors noted a growing trend toward empirically grounded applications of ABMS for innovation diffusion. Zhang and Vorobeychik (2019) conducted a critical review focused on empirically-grounded models, categorizing previous research by modeling methodologies and application domains. They identified that the key challenges for ABMS applications are model calibration and validation. Earlier reviews by Garcia (2005) and Dawid (2006) explored potential applications of agent-based modeling in innovation research and technological change, respectively. More recently, Scheller et al. (2019) synthesized the literature on empirically-grounded agent-based innovation diffusion models, offering insights into model development processes and suggesting future research directions. Lastly, Rand and Stummer (2021) provide a comprehensive review of the application of ABMS in the context of new product market diffusion. The authors focused on the strengths and criticisms of using ABMS for this purpose, discussing ABMS's advantages in capturing complex market diffusion processes and addressing common criticisms. The application of ABMS in innovation and market diffusion can be categorized into five areas: Technology-specific consumer adoption models, Network effects and social influence in diffusion, Market competition and strategic interactions, Policy design and intervention analysis, and Methodological advances and empirical integration. We present the results of our systematic review in the following groups.

3.8.1. Technology-specific consumer adoption models

Technology adoption decisions emerge from complex interactions between individual preferences, economic constraints, and social influences that traditional aggregate models cannot adequately capture. Research in this area utilizes ABMS to examine how heterogeneous consumer characteristics and decision-making processes aggregate to produce emergent patterns of adoption and market dynamics.

Energy technology adoption involves long-term investment decisions under uncertainty where multiple economic, environmental, and social factors interact to influence consumer choices. Research in this domain applies ABMS to model how household characteristics, financial constraints, and policy incentives combine to drive adoption decisions while accounting for the heterogeneous responses of different consumer segments. Meles and Ryan (2022) demonstrate the ability of ABMS in modeling heat pump technology adoption decisions. Their model captures how policy interventions interact with falling technology costs and subsidy reductions to drive adoption patterns. This application showcases ABMS's ability to model heterogeneous consumer responses to policy incentives while accounting for non-economic factors, such as social influence and individual attitudes, that traditional economic models often overlook. In another study, Schwarz and Ernst (2009) employ ABMS to model technology adoption decisions by simulating the diffusion of water-saving innovations among German households. The authors model households as heterogeneous agents with different lifestyle profiles such as postmaterialists, social leaders, traditionals, mainstream, and hedonistic milieus. Their model incorporates two decision-making algorithms: a cognitively demanding deliberate decision process and a simple "take-the-best" heuristic to reflect bounded rationality concepts. This model captures how household characteristics, social networks, and innovation characteristics combine to drive adoption decisions. This research showcases how ABMS can account for heterogeneous consumer responses while incorporating social learning and network effects that traditional econometric approaches often miss. Pakravan and MacCarty (2021) utilize ABMS to analyze the adoption of clean cookstoves in rural Uganda, demonstrating how spatial and temporal aspects of decision-making combine with social networks to influence technology diffusion patterns. The authors develop an agent-based model where individual households serve as autonomous agents making cookstove adoption decisions. In their model, agents communicate through small-world social networks that update dynamically over time and this model captures how individual psychological factors and rational economic decision-making interact to produce community-level adoption patterns. ABMS in this research enables addressing challenges in sustainable technology markets by helping designers and policymakers understand how social networks amplify both positive and negative technology experiences while informing strategies for achieving scalable adoption in resource-constrained environments.

Multiple studies focused on employing ABMS to model solar PV adoptions. Mohandes et al. (2019) apply ABMS to model residential solar PV adoption in Qatar's unique policy environment, characterized by heavily subsidized electricity and lack of traditional renewable energy incentives. The model simulates household agents (owners vs. renters) making adoption decisions based on economic competitiveness relative to subsidized electricity tariffs. In this research, ABMS captures how different policy scenarios impact adoption rates. This research demonstrates ABMS's capability to model technology adoption in contexts where traditional market mechanisms are distorted by subsidies, highlighting how ABMS can address emerging policy challenges in energy transitions. Rai and Robinson (2015) employ ABMS to model residential solar PV adoption using real-world data in Austin, Texas. The model integrates economic factors (household-level payback calculations), attitudinal components (based on Theory of Planned Behavior), and social networks (small-world networks with geographic and economic similarity). The research employs ABMS to demonstrate how social interactions and attitude evolution through the Relative Agreement algorithm create realistic adoption diffusion patterns. This application exemplifies ABMS's strength in capturing the multi-dimensional nature of technology adoption decisions while maintaining empirical grounding through detailed household-level data integration. In another study, Robinson and Rai (2015) systematically compare four ABMS variations of increasing complexity to understand which components are critical for accurate solar PV adoption modeling. The models range from "Economic Only" (purely financial decisions) to "Base-case" (full integration of economic, social, and attitudinal factors). The model utilizes the same data as in the Rai and Robinson (2015) study and demonstrates that while economic-only models capture aggregate adoption trends effectively, incorporating social networks and attitudinal factors becomes crucial for accurately predicting spatial and demographic adoption patterns. This research addresses key methodological challenges in ABMS by quantifying the value of model complexity and empirical data granularity, providing guidance for researchers on optimal model design for different research objectives in technology adoption studies. Stavrakas et al. (2019) develop a model that quantifies behavioral uncertainty in solar PV adoption decisions by Greek households. The authors model homeowners as heterogeneous agents with varying risk profiles, investment profitability beliefs, and resistance toward new technologies. Their model incorporates multiple layers of uncertainty through variance decomposition frameworks, distinguishing between input, parametric, and structural uncertainties. In this research, ABMS captures how initial beliefs, social learning through networks, financial constraints (payback periods, installation costs), and policy incentives (net-metering vs. self-consumption schemes) interact to influence adoption decisions.

The adoption of transportation technology creates complex decision dynamics where mobility needs, social acceptance, and infrastructure constraints interact with individual preferences and demographic characteristics. ABMS can examine how spatial and temporal aspects of mobility decisions combine with social networks and individual travel patterns to influence the diffusion of new transportation technologies. Dubey et al. (2022) develop an agent-based framework to forecast autonomous vehicle (AV) adoption by integrating consumer behavior modeling with population-level simulation. This study addresses technology adoption decisions in transportation markets, specifically examining how word-of-mouth communication and risk perceptions influence AV acceptance. Their model captures spatial effects through social networks based on geographic proximity and demographic similarity and demonstrates how information propagates through these networks to influence adoption decisions. This study illustrates how ABMS can evaluate policy interventions across heterogeneous consumer populations and offer insights for infrastructure planning and regulatory decisions in emerging technology markets. In another study, Wolf et al. (2015) introduce a model that combines cognitive science theories with ABMS to simulate EV adoption in Berlin. The model employs artificial neural networks based on emotional coherence theory, where agents make transport decisions by maximizing satisfaction across mental constraints, including needs, emotions, and social influences. This model identifies four distinct consumer types with varying responsiveness to policy interventions, revealing that exclusive zones for EVs can be more effective than financial incentives alone for certain market segments. This research demonstrates how ABMS can incorporate psychological realism into technology diffusion models and enable evaluation of diverse policy scenarios while accounting for the complex interplay between individual cognition, social influence, and spatial dynamics in transportation innovation adoption.

3.8.2. Network effects and social influence in diffusion

Network topology and communication patterns determine how information cascades through social systems, creating varying speeds and patterns of innovation diffusion depending on clustering, connectivity, and geographic factors. Research in this area employ ABMS to experiment with different network structures and communication mechanisms to understand how structural properties influence diffusion dynamics that would be impossible to test empirically. Bohlmann et al. (2010) demonstrate how ABMS can examine information cascades through social networks by modeling how network topology and relational heterogeneity affect innovation diffusion patterns. The authors employ ABMS to study heterogeneous individual agents interacting within different social network structures and examine how structural and relational heterogeneities provide an expanded lens for examining the diffusion process. Their model specifically addresses how clustering and connectivity influence diffusion dynamics. In another study, Delre, Jager, and Janssen (2007) employ ABMS to examine how information cascades create varying diffusion speeds depending on network structure and consumer heterogeneity. Their agent-based model includes consumer decision-making affected by social influences and word-of-mouth processes, where agents decide according to both individual preference and social influence from neighboring agents. This research demonstrates ABMS's ability to experiment with different network structures that would be impossible to test empirically. Delre et al. (2010) use ABMS to analyze how highly connected agents influence information cascades and innovation diffusion patterns. The authors developed an agent-based simulation model that integrates microlevel behaviors of consumers and macrolevel innovation diffusion, using more realistic agents and network structures than existing percolation models. Lengyel et al. (2020) demonstrate how ABMS can examine information cascades through social networks in geographical space using a Hungarian online social network. They develop an agent-based model where each agent has a set of neighbors from the empirical network structure. Their model incorporates complex contagion mechanisms in which the adoption of agents depends on the fraction of infected neighbors. In this study, ABMS reveals that geography plays a crucial role in complex contagion models, showing how physical distance and town size systematically bias adoption predictions across all model specifications. The agent-based approach enables examination of how local network properties (density, transitivity, modularity) interact with geographical factors to influence adoption timing and provides insights that are unattainable through traditional aggregate models.

Besides the network topology of consumer communication, opinion leadership has an impact on the adoption decision and patterns. Opinion leadership creates asymmetric influence patterns where certain individuals can disproportionately affect the adoption decisions of others through their network position and personal characteristics. Research in this field uses ABMS to examine how leader attributes, follower susceptibility, and network structure interact to determine when and how opinion leaders can successfully drive innovation diffusion. Van Eck et al. (2011) demonstrate how ABMS can examine the complex interplay between leader attributes, follower susceptibility, and network structure in driving innovation diffusion processes. The authors employ ABMS to investigate the critical role of opinion leaders in new product adoption, moving beyond simple network connectivity measures to incorporate multiple leader characteristics. Their model explicitly separates informational influence (product quality assessment) from normative influence (social pressure), allowing agents to make adoption decisions based on both utility thresholds and social dynamics. This study showcases ABMS's capacity to model how micro-level interactions between diverse agents with different capabilities and sensitivities produce emergent macro-level diffusion patterns, providing actionable insights for marketing strategy and innovation management.

3.8.3. Market competition and strategic interactions

Competitive markets create complex dynamics where firm strategies, consumer choices, and innovation diffusion interact through multiple feedback loops that can lead to unexpected market outcomes. Research in this category utilize ABMS to examine how strategic interactions between firms and heterogeneous consumer responses combine to influence adoption patterns in realistic competitive environments.

Competitive product diffusion generates complex choice dynamics where consumers evaluate multiple alternatives while being influenced by social networks, marketing activities, and evolving product characteristics. ABMS enables modeling how consumer comparison processes and repeat purchase behaviors interact with competitive strategies to determine market outcomes and diffusion patterns. Stummer et al. (2015) employ ABMS to model biofuel diffusion in the Austrian market and address the complex interplay between spatial distribution, social network, and consumer behavior. The authors develop an agent-based model in which consumer agents are distributed according to actual population density and they are connected through a spatially-explicit social network where communication probability depends on both geographic distance and social clustering. Moreover, their model captures temporal aspects through discrete event scheduling of communication, purchase, and post-purchase evaluation events. This research demonstrates how word-of-mouth communication travels through spatial social networks to influence technology adoption, showing that geographic proximity strongly correlates with social influence in innovation diffusion. In another study, Shi et al. (2020) utilize ABMS to model competitive technology adoption decisions where enterprises continuously evaluate between low-carbon and conventional technologies. They simulate 300 enterprise agents engaged in evolutionary games where firms compare payoffs with influential neighbors and update their technology choices accordingly. In this study, ABMS captures dynamic competitive interactions where enterprises' adoption decisions create feedback effects through the network. This research showcases ABMS's ability to model how competitive comparison processes and repeated strategic decisions interact with external interventions to produce unexpected market outcomes, demonstrating that competitive markets can dilute targeted policy effects through complex interdependencies. Lastly Shi et al., (2021), demonstrate how ABMS can model competitive technology adoption through two-level heterogeneous social networks, where enterprises and consumers interact across different network structures to determine market outcomes. Their model captures competitive dynamics between low-carbon and conventional products where enterprises continuously evaluate switching strategies based on profit comparisons with network neighbors, while consumers' purchasing patterns create demand fluctuations that influence enterprise decisions. This research presents the ability of ABMS to model how competitive comparison processes between alternative technologies combine with consumer repeat purchase behaviors and policy interventions to determine long-term market diffusion patterns and competitive equilibria.

3.8.4. Policy design and intervention analysis

Different policy instruments influence innovation diffusion patterns. The research in this group examines ABMS to study this influence and how consumer heterogeneity can lead to differential policy effectiveness across population segments. Dawid et al. (2014) employ ABMS to examine regional economic convergence by modeling heterogeneous firms and households across two regions with different technological and skill endowments. Their model demonstrates how spatial labor mobility interacts with social networks and individual firm decisions to influence technology adoption patterns. This model captures how human capital and technology policies affect convergence differently depending on labor market integration levels. This research shows how ABMS can model complex feedback loops between individual decisions and aggregate outcomes while highlighting the importance of considering temporal aspects (short vs. long-term policy effects) and spatial mobility patterns. Kowalska-Pyzalska et al. (2014) utilize ABMS to study dynamic electricity tariff adoption by modeling agents with heterogeneous opinion formation processes influenced by social networks, indifference levels, and external advertising. This model incorporates spatial networks (grid topology) where agents' decisions are influenced by unanimous neighborhood opinions, external fields (advertising), and individual indifference levels. Critically, they model the temporal delay between opinion formation and actual adoption decisions. In this study, the spatial conformity effects and temporal decision requirements combine to create realistic adoption patterns and demonstrate how individual indifference levels can prevent technology diffusion even with strong external promotion.

3.9. Market vulnerability and crises

Market vulnerability and crises in financial markets emerge from complex interactions between heterogeneous market participants, institutional structures, and behavioral dynamics that traditional economic models struggle to capture. Research in this area utilizes ABMS to examine how localized disturbances propagate through financial networks, how policy interventions affect crisis dynamics, and how behavioral feedback loops can generate endogenous instability. These models reveal that crisis severity often depends more on market participants' reactions to initial shocks than on the magnitude of the shocks themselves, which highlights the role of network effects, sentiment contagion, and institutional responses in determining systemic outcomes. It is worth noting that, as shown in Table 1, the volume of ABMS literature specifically targeting "crises" and "vulnerability" is smaller compared to more established areas like consumer behavior or pricing strategies. This observation reflects the relatively recent adoption of agent-based methods for systemic risk analysis, catalyzed mainly by the limitations of traditional models exposed during the 2008 financial crisis. The application of ABMS to market vulnerability and crises can be organized into three interconnected subcategories that collectively provide a comprehensive understanding of financial system fragility: Systemic Risk and Financial Network Contagion, Crisis Resolution Mechanisms and Policy Responses, and Endogenous Crisis Dynamics and Behavioral Mechanisms. These categories form a logical progression from understanding structural vulnerabilities to examining policy interventions and finally exploring the fundamental behavioral drivers of crisis emergence.

3.9.1. Systemic risk and financial network contagion

Financial interconnectedness creates dual dynamics where risk-sharing benefits under normal conditions transform into contagion pathways during stress periods. Research in this area utilizes ABMS to examine how network structures among financial institutions facilitate both liquidity provision and systemic risk propagation, revealing non-monotonic relationships between connectivity levels and system stability that challenge traditional risk-sharing assumptions. Bookstaber et al. (2018) develop an agent-based model for analyzing the vulnerability of the financial system to asset- and funding-based fire sales. In this research, authors employ ABMS to model the complete funding ecosystem to capture the dynamic interactions of agents in the financial system, extending from the suppliers of funding through the intermediation and transformation functions of the bank/dealers to the financial institutions that use the funds to trade in the asset markets. ABMS in this study captures the dynamic and sequential interaction of agents to initial losses rather than just the losses themselves. The model demonstrates how individual bank choices create feedback loops and cascading effects that would be impossible to capture with static equilibrium models. Grilli et al. (2015) apply ABMS to explore interbank connectivity effects on financial contagion and business cycle fluctuations. The research reveals a non-monotonic relationship between bank connectivity and system performance, where connectivity initially reduces systemic risk through risk sharing, but beyond an optimal threshold, it increases systemic risk due to contagion effects. This finding directly challenges the linear risk-sharing assumptions in traditional banking models. Liu et al. (2020) develop a 1:1 scale agent-based model of the U.S. banking system using 6600 banks' quarterly balance sheets from real-world data. In this model, banks make lending and borrowing decisions based on target financial ratios and use scoring systems combining size scores and relationship scores to select counterparties. In this study, ABMS demonstrates that endogenous network formation fundamentally changes contagion dynamics compared to static network models.

3.9.2. Crisis resolution mechanisms and policy responses

Policy interventions during financial crises generate complex interactions between regulatory actions and market participant behavior that can either stabilize or further destabilize the system. Research in this area utilizes ABMS to evaluate how different crisis resolution strategies perform under varying economic conditions while accounting for the dynamic feedback effects between policy measures and agent responses. Dosi et al. (2015) develop an agent-based model to analyze interactions between fiscal and monetary policies in an economy with heterogeneous interacting agents to evaluate how different crisis resolution strategies perform under varying economic conditions. In this research, ABMS captures dynamic feedback effects where fiscal consolidation becomes self-defeating during recessions, contradicting the intended policy outcomes. The model's ability to simulate far-from-equilibrium dynamics with genuine agent heterogeneity reveals how policy effectiveness varies dramatically across different economic regimes, providing insights that would be impossible to obtain from representative agent models. Klimek et al. (2015) employ the framework of the Mark I CRISIS model developed within the CRISIS project[1] to examine three distinct crisis resolution mechanisms: Purchase & Assumption, government bail-outs, and bail-ins with private sector involvement. Their model reveals that optimal crisis resolution strategies are highly dependent on prevailing economic conditions. The model demonstrates how the same policy intervention can have dramatically different outcomes depending on the economic state, with different resolution mechanisms creating distinct feedback loops between the financial and real sectors. This state-contingent nature of policy effectiveness, captured through the dynamic interactions of heterogeneous agents, highlights the critical importance of adaptive policy design and challenges "one-size-fits-all" approaches to financial crisis resolution that are common in traditional economic models. Lamperti et al. (2019) employ Dystopian Schumpeter meeting Keynes model (Lamperti et al., 2018) to incorporate climate damages affecting firm productivity, creating a comprehensive agent-based framework that simulates interactions between heterogeneous households, firms, energy plants, banks, and policymakers under climate-induced shocks to labor productivity and capital stocks. Their research quantifies how climate change amplifies financial instability, and the model captures the dynamic feedback loops between climate damages, firm bankruptcies, banking sector health, and subsequent credit crunches that amplify real economic impacts. This research demonstrates how ABMS can address emerging, complex challenges by modeling multi-system interactions between climate, economy, and finance that traditional approaches cannot adequately capture.

3.9.3. Endogenous crisis dynamics and behavioral mechanisms

Market sentiment and behavioral dynamics can generate financial instability through self-reinforcing feedback loops that operate independently of external shocks. Research in this area utilizes ABMS to examine how psychological factors, sentiment contagion, and adaptive expectations interact with balance sheet dynamics to create endogenous cycles of instability that emerge from the collective behavior of market participants. Lorscheid et al. (2019) advocate for advancing ABMS from case-specific applications to general theory development, specifically emphasizing how agent-based models can capture endogenous crisis dynamics that emerge from the behavioral mechanisms of interacting agents rather than external shocks. The authors demonstrate how ABMS addresses market vulnerability by modeling heterogeneous agents with bounded rationality who create endogenous feedback loops between micro-behavioral decisions and macro-level crisis patterns. Moreover, they show how individual adaptive behaviors and local interactions can spontaneously generate system-wide instabilities and regime shifts. Their framework enables exploration of how behavioral mechanisms create intricate systems of interdependent feedback loops that can lead to sudden transitions from stability to crisis states. Seppecher and Salle (2015) develop a fully decentralized macroeconomic model with 5000 heterogeneous households and 550 firms to examine psychological factors and sentiment contagion by developing a macroeconomic model with opinion dynamics where market sentiment (optimistic or pessimistic) spreads through herding behavior and directly affects agents' financial decisions. The authors employ ABMS to model endogenous financial behavior where agents adjust their leverage and precautionary saving decisions based on sentiment contagion, creating a stock-flow consistent framework where all balance sheets are interconnected and prices/wages emerge from decentralized market interactions. Their model captures complex behavioral mechanisms through procedural rationality, where agents use satisficing rules and adaptive heuristics rather than optimization, allowing the model to generate self-reinforcing feedback loops between sentiment, financial decisions, and aggregate outcomes without any exogenous shocks. This research demonstrates ABMS's capability to model how psychological factors and adaptive expectations interact with balance sheet dynamics through sequential decision-making processes that create emergent boom-bust cycles, debt-deflation spirals, and recovery dynamics that arise purely from the collective behavioral interactions of boundedly rational agents responding to their local information and social influences.

3.10. Market impact and volatility

Market impact and volatility represent fundamental aspects of financial market dynamics that emerge from complex interactions between heterogeneous agents operating under various constraints and behavioral patterns. Market impact refers to the price change caused by trading activities, measuring how individual or institutional trades affect asset prices, while volatility captures the degree of price fluctuation over time, reflecting market uncertainty and risk. ABMS enables analyzing these phenomena by modeling the micro-level interactions that give rise to macro-level market volatility and price impact patterns. Similar to the domain of market vulnerability, the application of ABMS to volatility remains a specialized field with a more concentrated body of literature compared to broader market decision areas. The research presented here represents the key methodological contributions that have successfully linked micro-structural market mechanisms to aggregate volatility patterns. The application of ABMS for analyzing market impact and volatility can be categorized into four main areas: Behavioral Foundations and Agent Interactions, Market Microstructure and Order Flow Dynamics, Market-Specific Applications and Specialized Dynamics, and Regulatory Interventions and Market Optimization. Behavioral Foundations and Agent Interactions examines the psychological and social mechanisms that drive individual and collective trading decisions, establishing the micro-level behavioral patterns that underlie all market volatility phenomena. Market Microstructure and Order Flow Dynamics investigates how these behavioral patterns translate into specific trading mechanisms and price formation processes through order book dynamics and market clearing mechanisms. Market-Specific Applications and Specialized Dynamics demonstrates how general behavioral and microstructural principles manifest across different market contexts, from cryptocurrency mining to land use change. Regulatory Interventions and Market Optimization explores how external policies and specialized strategies can modify the behavioral-microstructural system to achieve desired stability and efficiency outcomes.

3.10.1. Behavioral foundations and agent interactions

Herding behavior and strategy switching create cascading effects that amplify individual trading decisions into system-wide volatility patterns. Research in this area utilizes ABMS to model how social interactions and psychological biases among traders generate the fundamental behavioral dynamics that drive market instability and impact transmission mechanisms. Alfarano et al. (2005) employ ABMS to model financial market dynamics through an asymmetric herding mechanism where agents switch between fundamentalist and noise trader strategies based on social interactions and autonomous tendencies. Their model simulates how heterogeneous traders with different behavioral biases interact through herding behavior. In this model, agents have asymmetric transition probabilities between trader types, which enable the model to capture how psychological biases and social influence create return distributions and volatility clustering in observed real financial markets. This research demonstrates the ABMS's ability to show how simple behavioral rules and social interactions at the micro level can generate complex emergent phenomena like market instability, providing insights into how behavioral contagion spreads through markets and contributes to systemic risk. Chen et al. (2015) develop an agent-based model with multi-level herding mechanisms operating simultaneously at stock, sector, and market levels to investigate how social interactions create both spatial and temporal market correlations. Their model represents herding behavior that cascades from individual stock decisions to sector-wide movements to market-wide phenomena. The multi-level structure of this model captures how psychological biases and social influence propagate through different organizational scales of the market and reproduce sector structure (spatial correlations) and volatility clustering (temporal correlations) observed in real markets like the NYSE and Hong Kong Stock Exchange. This research demonstrates how ABMS can model the complex transmission mechanisms through which behavioral contagion operates across market hierarchies, revealing how individual trader psychology and social interactions aggregate to create systemic market behaviors and cross-market spillover effects.

3.10.2. Market microstructure and order flow dynamics

Order flow patterns and market clearing mechanisms transform behavioral impulses into observable price movements and volatility clustering through the technical architecture of trading systems. Research in this area utilizes ABMS to examine how different trading technologies, frequency patterns, and market structures convert agent behaviors into measurable market impact and price discovery processes. Farmer et al. (2005) employ ABMS to model continuous double auction markets using minimally intelligent agents that place orders randomly subject to price constraints, challenging traditional rational agent assumptions in financial markets. Their model includes impatient agents placing market orders via Poisson processes and patient agents placing limit orders uniformly across price intervals, treating the statistical mechanics of order placement and price formation within limit order book structures. This research demonstrates how simple agent behavior can generate complex market phenomena. This methodology addresses decision areas in price discovery mechanisms and market microstructure dynamics while providing a benchmark for separating institutional effects from strategic behavior, offering a foundation for understanding how different trading technologies and market structures convert basic agent interactions into measurable market outcomes. Jacob Leal et al. (2016) develop an agent-based model that combines chronological and event-time trading frameworks to study interactions between low-frequency and high-frequency traders using different strategies. Their model focuses on trading frequency, order timing strategies, and market liquidity provision by demonstrating how different temporal trading paradigms interact to generate market volatility and flash crashes through three specific mechanisms. This research demonstrates ABMS's capability to capture how technological advantages in speed and information processing create complex feedback loops between trader types. This modeling approach also enables authors to evaluate trade-offs between market stability and efficiency while assessing the impacts of emerging trading technologies on price discovery processes.

3.10.3. Market-specific applications and specialized dynamics

Different market contexts impose unique constraints and mechanisms that modify how general behavioral and microstructural principles manifest in specific trading environments. Research in this area utilizes ABMS to investigate how market-specific factors such as mining processes in cryptocurrency markets, spatial constraints in land markets, and climate variability in agricultural markets create distinctive volatility and impact patterns. Cocco and Marchesi (2016) employ ABMS to analyze the economics of Bitcoin mining by modeling heterogeneous agents with different market-based decision-making behaviors. Their model incorporates key market elements including budget constraints and competitive bidding to capture how mining processes create distinctive market dynamics. The simulation demonstrates how mining hardware evolution (from CPUs to GPUs to ASICs) and associated costs affect Bitcoin generation, hashing capability, and power consumption. This research reveals how mining-specific factors like hardware obsolescence and electricity costs create unique volatility patterns in cryptocurrency markets that differ from traditional financial markets. In another study, Cocco et al. (2017) utilize ABMS to study cryptocurrency markets by creating an artificial Bitcoin market with heterogeneous agents. Their model captures the unique characteristics of cryptocurrency markets including Bitcoin mining processes (where the number of Bitcoins increases over time proportionally to real mining rates), market-based price formation through order books, and the entry/exit of new traders representing real-world adoption patterns. Using ABMS enabled authors to reproduce key stylized facts of Bitcoin markets, including unit root properties, fat tail phenomena, and volatility clustering. The agent-based approach allowed them to demonstrate how individual trading behaviors and mining processes aggregate to create system-level market patterns. Sun et al. (2014) apply ABMS to investigate land-use change in North American urban-rural fringe areas, focusing on how market mechanisms shape spatial development patterns. Their model incorporates spatial constraints through monocentric city design, heterogeneous agents (rural landowners and residential households), and realistic market mechanisms including budget constraints and competitive bidding. In this study, ABMS allowed them to conduct controlled experiments comparing different market representation levels. This approach enabled them to demonstrate how individual location decisions aggregate into emergent urban development patterns. Wossen et al. (2018) employ an agent-based modeling platform to assess the impacts of climate and price variability on household income and food security in Ethiopia and Ghana. Their model captures climate-specific factors by incorporating historical rainfall patterns, seasonal price variations, and diverse adaptation strategies while modeling heterogeneous farm households with different resource endowments and risk preferences. In this research, the authors compare scenarios with and without climate variability, and test different adaptation strategies in a controlled environment using ABMS. The agent-based approach allowed them to capture the distributional effects of climate shocks and evaluate how different policy interventions could reduce vulnerability across different household types.

3.10.4. Regulatory interventions and market optimization

Policy interventions and specialized trading strategies create dynamic feedback loops with existing market mechanisms that can either stabilize or destabilize the underlying behavioral-microstructural system. Research in this area utilizes ABMS to examine how regulatory measures such as trading halts, transaction taxes, and minimum resting times interact with agent behaviors and market structures to modify volatility patterns and market impact dynamics. Leal and Napoletano (2019) employ ABMS to analyze regulatory policies targeting high-frequency trading by modeling a limit-order book market with heterogeneous traders. Their agent-based approach captures emergent phenomena like flash crashes that arise from trader interactions, while simultaneously evaluating how regulatory policies modify these dynamics. In this study, ABMS reveals trade-offs between market stability and resilience that would be impossible to identify through traditional analytical methods. This research showcases how ABMS can inform regulatory policy design by indicating unintended consequences and complex feedback effects between rules and market participant behaviors. Westphal and Sornette (2020) use ABMS to examine how sophisticated trading strategies impact market dynamics by introducing agents with advanced bubble detection capabilities alongside traditional traders types. Their model demonstrates how ABMS can capture non-linear market effects and show that the same mechanisms promoting market efficiency can become sources of instability as market conditions change. This research highlights ABMS's ability to model the evolution of market structure over time, revealing optimal thresholds for different trader types and demonstrating how agent-based approaches can address emerging challenges in financial markets by incorporating cutting-edge trading technologies and their systemic implications.

4. Challenges and opportunities of employing ABMS

The systematic literature review in Section 3 demonstrates the versatility and potential of ABMS across nine distinct application areas in economic and financial markets. However, implementing and applying ABMS in economic research is not without challenges. At the same time, the ongoing development of ABMS techniques and the increasing availability of data and computational resources present opportunities for advancing our understanding of economic markets. In a comprehensive review, An et al. (2021) examine the evolutions and discuss the challenges and opportunities of ABMS applications in ecological, social, and social-ecological systems. Despite focusing on other domains beyond economics, their review of ABMS challenges such as model validation, behavioral representation, and integration of machine learning techniques, provides methodological insights that are practical for the employment of ABMS in economics and finance. In this section, we discuss the key challenges and opportunities associated with applying ABMS in economic and financial markets to provide a clear understanding of the current limitations of ABMS while inspiring future research directions in this field.

This section begins with a discussion of the common challenges and opportunities across various applications of ABMS in economic markets. Then, it focuses on category-specific challenges and opportunities corresponding to the market analysis domain explored in Section 3. Finally, it will present a discussion aiming to identify overall trends and future research directions of the research and application of ABMS in economic and financial markets.

4.1. Common challenges

The application of ABMS in economic and financial markets faces several interconnected challenges that span across all decision areas identified in this review. These challenges fundamentally impact the reliability, validity, and practical applicability of ABMS results in market analysis and decision support.

4.1.1. Computational complexity and scalability

The computational demands of ABMS present significant challenges for its practical implementation and application. Aliabadi et al. (2017) report simulation studies requiring over 700 hours on powerful computers for comprehensive analysis, while highlighting trade-offs between model detail and computational feasibility. Awwad et al. (2015) note that trade-offs must be made between computational cost and behavioral convergence, with full-scale simulations taking substantial computational time even on high-performance computers.

Lussange et al. (2021) acknowledge that action-state spaces of reinforcement learning algorithms must be highly discretized and handcrafted primarily to limit necessary computational resources. As models incorporate more heterogeneous agents and complex interactions, computational requirements increase significantly, limiting the scale and scope of analysis that can be conducted within reasonable timeframes (Cardaci, 2018).

4.1.2. Model validation and verification complexity

Establishing the credibility of agent-based models simulation results presents unique challenges due to the complexity of agent-based systems and the difficulty of obtaining comprehensive real-world data for comparison (Awwad & Ammoury, 2019). Baindur and Viegas (2011) note that most existing models adopt a micro-level approach aimed at private policy analysis, which is complicating validation efforts. The challenge encompasses both individual agent behaviors and emergent system-level properties, requiring validation at multiple levels simultaneously.

Lussange et al. (2021) address this challenge by calibrating their model with real market data from the London Stock Exchange, demonstrating the importance of empirical grounding. However, Lorscheid et al. (2019) identify concerns about internal validity and the ability to understand complex agent-based models, noting skepticism about drilling down to determine which assumptions are responsible for conclusions and discerning causal connections between initial conditions and results.

Furthermore, recent literature has formalized a hierarchical set of validation protocols specifically for economic ABMS to address these challenges. Fagiolo et al. (2019) argue that validation must move beyond simple output matching to a history-friendly approach that replicates the statistical properties of empirical time series (stylized facts) while ensuring the model's causal mechanisms are theoretically sound. Guerini and Moneta (2017) propose a "causal validation" methodology, which uses Structural Vector Autoregression on simulated data to verify that the model's internal transmission channels match those observed in real economic data, rather than just matching aggregate trends. To bridge the gap between micro-rules and macro-outcomes, Bektas et al. (2021) introduce a meso-level validation approach, demonstrating (using a mobility case) that validating group-level behaviors provides a critical intermediate check that prevents correct macro-results from emerging for the wrong micro-reasons.

4.1.3. Parameter calibration and sensitivity

A persistent challenge across all ABMS applications is the sensitivity of model outcomes to parameter choices and the difficulty of calibrating models to real-world data. Awwad and Ammoury (2019) highlight that model outcomes exhibit significant sensitivity to parameter choices, particularly when modeling heterogeneous agents with different behavioral rules and adaptation mechanisms. This challenge is compounded by the fact that many numerical assumptions for parameters are chosen hypothetically and can be easily modified to reflect different market conditions. Poledna et al. (2023) point out the "wilderness of bounded rationality" (Sims, 1980), which refers to criticism that agent-based models have too many degrees of freedom and parameters to calibrate that potentially allows to match any observed pattern in real data to an agent-based model through parameter adjustment (Fagiolo & Roventini, 2012).

This challenge extends beyond mere parameter identification to encompass comprehensive sensitivity analysis. Aliabadi et al. (2017) demonstrate the methodological rigor required, conducting extensive sensitivity analysis across 2601 different parameter combinations to ensure robust results. Similarly, Raberto et al. (2019) emphasize the need to monitor model sensitivity to certain hyperparameter ranges, especially in areas of non-linearity with respect to real data calibration.

Recent literature has shifted toward automated, data-driven frameworks that prioritize uncertainty quantification and simulation efficiency to address these calibration complexities and computational constraints. Platt (2020) systematically compares calibration techniques and finds that while frequentist approaches like Simulated Minimum Distance (SMD) are common and computationally cheaper, Bayesian estimation methods offer superior robustness in recovering true parameters. Kim et al. (2021) consider evolving market conditions and challenge the assumption of static parameters, developing a framework for automatically calibrating dynamic, heterogeneous parameters that employs Hidden Markov Models and Gaussian Process Regression to adaptively adjust parameters in response to temporal regime shifts and agent clustering. To mitigate the computational burden of high-dimensional parameter estimation, McCulloch et al. (2022) propose a hybrid framework that uses History Matching to rapidly rule out implausible parameter spaces before applying Approximate Bayesian Computation (ABC), thereby enhancing calibration efficiency without sacrificing robustness. Most recently, Dyer et al. (2024) introduce "black-box" simulation-based inference methods using neural posterior estimation and neural ratio estimation, which decouple inference from simulation to handle non-stationary, multivariate time-series data more effectively than traditional ABC methods.

4.1.4. Behavioral rule specification and bounded rationality

Determining appropriate behavioral rules for different agent types remains a significant challenge across all ABMS applications. Fagiolo et al. (2004) emphasize that these rules must balance realism with computational tractability while avoiding oversimplification of complex decision-making processes. The challenge includes deciding between gradient-based adaptation rules versus optimizing decision rules, each with different implications for model dynamics (BenDor et al., 2009).

The literature consistently acknowledges that modeling human behavior using formal models is challenging, particularly given that most agent-based models assume agents are rational decision makers, despite the lack of widely accepted modeling methods for more accurately capturing human behavior (Scalco et al., 2019). This challenge is particularly acute when attempting to integrate insights from behavioral economics while maintaining model parsimony. In addressing the challenge of defining adaptive behaviors under uncertainty, insights can also be drawn from adjacent fields. For instance, Cheng, Yu, et al. (2025) employ Evolutionary Game Theory to model decentralized decision-making in renewable energy systems, illustrating how evolutionary dynamics can serve as a robust comparative framework for capturing how agents adapt strategies in distributed, uncertain environments.

The specification of behavioral rules also raises fundamental concerns regarding the generalization of agent-based models across different market regimes, which is a challenge parallel to the "Lucas Critique" in macroeconomics. If agents are assigned static heuristics calibrated to a specific historical period, the model risks "overfitting" and failing to replicate dynamics during structural breaks or unprecedented events. This creates what Poledna et al. (2023) refer to as the "wilderness of bounded rationality", where the degrees of freedom in defining agent behavior are vast. As noted by Fagiolo et al. (2019), models must achieve "structural validity", meaning the micro-level rules must remain robust even when macro-conditions shift. While Dosi and Roventini (2019) argue that ABMS is theoretically immune to the Lucas Critique because it models deep invariant micro-foundations, this validity depends heavily on the model's ability to capture genuine adaptive learning. Recent integrations of Reinforcement Learning (Lussange et al., 2021) offer a promising solution by allowing agents to autonomously evolve their strategies, though validating these complex adaptive mechanisms remains a significant challenge.

4.1.5. Data requirements and availability

A persistent challenge across all applications is the substantial data requirements for model parameterization and validation, coupled with the limited availability of high-quality empirical data. Van Heeswijk et al. (2019) illustrate this challenge by combining data from multiple literature sources with expert interviews to cross-validate parameter estimates for their urban consolidation center model. Scalco et al. (2019) note that specific data on probability distributions of consumer susceptibility often does not exist, requiring researchers to make assumptions based on theoretical suggestions.

Moglia et al. (2018) identify the lack of reliable data to feed models attempting to mimic agent behavior as one of the main ABMS limitations. This challenge is particularly pronounced for disaggregated behavioral data that is often unavailable in standard datasets, forcing researchers to rely on proxy data from different contexts or make simplifying assumptions about agent behaviors.

4.1.6. Integration of heterogeneity and model complexity

Capturing the full range of individual differences while maintaining model parsimony presents a common challenge across consumer behavior applications (Dulam et al., 2021). Dehghanpour and Nehrir (2017) address heterogeneity by modeling different types of agents with distinct objective functions, but the challenge of adequately representing heterogeneity without overwhelming computational complexity persists.

Cross-disciplinary insights reinforce the importance of this challenge. As noted by Cheng, Li, et al. (2025) in the context of urban energy systems, modeling heterogeneous agents that are characterized with distinct multi-objective optimization functions and dynamic behaviors is critical for accurately capturing socio-economic interactions. This parallel underscores that effectively handling agent heterogeneity is a universal requisite for realistic market simulation, whether in decentralized energy networks or financial markets.

The tension between model realism and tractability represents a fundamental trade-off in ABMS applications. Poledna et al. (2023) acknowledge that models do not represent every step in complex supply chains, while Riddle et al. (2021) note that data sparsity limits the capability to capture all variability and uncertainty across supply chains. This creates ongoing challenges in determining appropriate levels of model complexity that balance representational accuracy with analytical tractability.

4.1.7. Emergent behavior analysis and interdisciplinary integration

The complexity of agent-based models can obscure causal mechanisms, making it harder for decision-makers to interpret results or trace the impact of specific interventions (Riccetti et al., 2018). Successfully applying ABMS to market analysis requires integration of knowledge from economics, psychology, sociology, and computer science, making model development resource-intensive and dependent on multi-domain expertise (Kashani et al., 2019).

Lorscheid et al. (2019) use O'Sullivan et al. (2016) term "yet another model syndrome", to describe the current situation, referring to the presentation of model after model without accumulating general theoretical insights into systems and their dynamics. This limitation in theory development represents a significant challenge for the field's advancement and practical application in decision support contexts.

These challenges collectively represent barriers to the widespread adoption and acceptance of ABMS in economic and financial analysis. However, they also point toward important areas for methodological development and innovation in the field, as researchers continue to develop more sophisticated approaches to address these fundamental limitations while leveraging the unique insights that ABMS can provide for understanding complex market dynamics.

4.2. Common opportunities

ABMS presents multiple opportunities for advancing research and practice in the fields of economics and finance. These opportunities span methodological innovations, analytical capabilities, and practical applications that collectively enhance our understanding and management of complex market systems. These opportunities can be categorized into the following domains:

4.2.1. Emergent phenomena and complex systems understanding

One of the most significant opportunities offered by ABMS is its ability to capture emergent phenomena that arise from agent interactions without requiring top-down coordination (BenDor et al., 2009; Fagiolo et al., 2004). Unlike traditional economic models that impose top-down structures, ABMS enables researchers to observe how macro-level market regularities and stylized facts spontaneously emerge from individual agent behaviors without explicit programming (Poledna et al., 2023). This capability proves particularly valuable for understanding complex market dynamics where Lussange et al. (2021) demonstrate how agent learning enables accurate emulation of market microstructure as an emergent property of multi-agent systems. The ability to model non-equilibrium dynamics and capture tipping points, herd behavior, and cascading failures represents a fundamental advantage over traditional equilibrium-based models (Kashani et al., 2019).

ABMS enables the study of non-equilibrium dynamics and tipping points, capturing phenomena such as market freezes, leverage cycles, and crisis cascades that are characteristic of real-world financial markets (Popoyan et al., 2020; Riccetti et al., 2018). This capability is particularly valuable for understanding how small changes in market conditions or trader behavior can lead to dramatically different system-level outcomes.

4.2.2. Heterogeneity modeling and realistic market representation

ABMS provides unprecedented opportunities for modeling agent heterogeneity, moving beyond the limitations of representative agent models to capture realistic diversity in market participants (Baindur & Viegas, 2011; Fagiolo et al., 2004). This heterogeneity encompasses differences in capabilities, preferences, strategies, and behavioral patterns that significantly affect market outcomes and system stability. He et al. (2016) demonstrate how modeling heterogeneous customer agents with uncertainty about service quality enables a better understanding of market dynamics across different user types. This capability extends to modeling diverse sub-population responses to economic signals and regulatory interventions, facilitating more inclusive and targeted policy design (Kashani et al., 2019).

The methodology supports the integration of behavioral realism, which traditional economic models often overlook, by incorporating factors such as herding behavior, momentum trading, and social influence mechanisms (Scalco et al., 2019; Vidal-Tomás & Alfarano, 2020). This enhanced behavioral representation enables exploration of sub-population responses to economic signals and regulatory interventions, leading to more inclusive and targeted policy design.

4.2.3. Dynamic interaction and learning mechanisms

The ability to model dynamic interactions between agents over time represents another opportunity (Baindur & Viegas, 2011). ABMS enables the capture of learning, adaptation, and co-evolution of strategies in ways that static models cannot accommodate, allowing for an understanding of how market structures and participant behaviors co-evolve in response to changing conditions (BenDor et al., 2009). Dehghanpour and Nehrir (2017) and Poplavskaya et al. (2020) demonstrate integration of machine learning techniques for agent decision-making and system-level optimization, suggesting broader applicability for incorporating advanced AI techniques across various economic modeling domains.

4.2.4. Multi-scale and multi-level analysis

ABMS enables integration of multiple decision levels, from individual agent choices to market-level outcomes, providing opportunities to understand how decisions at different scales interact and influence overall system behavior (Baindur & Viegas, 2011;

Fagiolo et al., 2004). This multi-level integration proves particularly valuable for understanding complex systems where individual, organizational, and systemic factors all play important roles. The ability to bridge micro and macro analysis consistently emerges across decision areas, as demonstrated by Riddle et al. (2021), who show how agent-based models can capture dynamic, non-linear market responses to disruptions while explicitly modeling individual decision-making agents.

4.2.5. Policy experimentation and strategic decision support

ABMS can serve as a virtual laboratory for policy testing and strategic decision support, offering opportunities to evaluate interventions before real-world implementation (Awwad et al., 2015; Baindur & Viegas, 2011). This capability is particularly valuable for understanding potential consequences and unintended effects of various regulatory approaches. Vinogradov et al. (2020) demonstrate how moderate taxation creates more stable markets than time-based restrictions in sharing economy regulation, which contributes to systematic policy learning through controlled experimentation. The methodology enables policymakers to explore different scenarios and market designs and act as evidence-based tools for regulatory analysis across various economic sectors.

4.2.6. Advanced computational capabilities and real-time applications

The integration of advanced computing capabilities presents opportunities for more sophisticated and realistic models (Poledna et al., 2023). Distributed optimization approaches, as demonstrated by Dehghanpour and Nehrir (2017), offer opportunities for creating realistic and scalable models where centralized control is neither realistic nor desirable. ABMS frameworks can be adapted for real-time applications across various economic domains, with rolling horizon optimization schemes providing computational efficiency for operational decision support systems.

4.2.7. Scenario analysis and risk assessment

ABMS provides opportunities for conducting comprehensive what-if scenario analyses. This ability enables researchers and policymakers to examine the potential consequences of various interventions, market structures, or external shocks (Awwad & Ammoury, 2019; Baindur & Viegas, 2011). This capability is specifically valuable for policy design and risk assessment in complex market environments. Agent-based models demonstrate robustness across diverse financial markets, supporting generalizability and enabling stress testing under various market conditions and trader compositions (Bookstaber et al., 2018; Vidal-Tomás & Alfarano, 2020).

4.2.8. Behavioral realism and market psychology

ABMS offers the ability to incorporate behavioral realism, which is often overlooked by traditional economic models (Lorscheid et al., 2019). The ability to model bounded rationality, heterogeneous preferences, and adaptive learning provides more realistic representations of market participants. This includes capturing psychological factors such as herding behavior, momentum trading, and other behavioral biases that significantly influence market dynamics but are challenging to incorporate into traditional models.

These diverse opportunities collectively position ABMS as a powerful and flexible methodology for advancing understanding of economic and financial markets, supporting both theoretical development and practical decision-making in an increasingly complex and interconnected global economy.

4.3. Category-specific challenges and opportunities

Beyond the general methodological considerations, each specific area of market analysis presents unique challenges and opportunities for ABMS implementation. This section examines the domain-specific considerations across the nine decision areas identified in our systematic review, while mentioning both the constraints researchers face and the distinctive capabilities ABMS offers in each context.

4.3.1. Economic forecasting and market dynamics

Economic forecasting through ABMS faces several distinctive challenges. The complexity of modeling realistic bidding processes presents significant difficulties, particularly in construction markets where contractors must make decisions under uncertainty with incomplete information about competitors' strategies (Awwad & Ammoury, 2019). A fundamental tension exists between modeling systems that seek equilibrium states and those that operate in persistent disequilibrium conditions, where aggregate regularities emerge from decentralized interactions and imperfect coordination (Fagiolo et al., 2004). Additionally, the integration of multi-modal transport competition requires capturing complex interactions between supply and demand dynamics, infrastructure constraints, and policy interventions (Baindur & Viegas, 2011).

Model validation presents ongoing challenges, as the sparsity of data limits the capability to capture variability and uncertainty in agent decision behaviors across supply chains (Poledna et al., 2023). The extensive data requirements for parameter calibration compound these difficulties, often requiring integration of national accounts, sector accounts, input-output tables, and detailed project-specific data (Poledna et al., 2023). Computational complexity becomes substantial, with some studies requiring 1000 simulations using high-performance computing resources to capture parameter uncertainties (Riddle et al., 2021).

Despite these challenges, ABMS offers unique opportunities for economic forecasting. This modeling approach enables bottom-up modeling of diverse, complex business-driven decisions that adapt based on market signals (Poledna et al., 2023). Policymakers benefit from the ability to assess medium-run macroeconomic effects of different scenarios, such as lockdown measures, before implementation (Poledna et al., 2023). The detailed structure of agent-based models enables disaggregated forecasting and sectoral analysis, offering insights into the composition of overall macroeconomic trends (Poledna et al., 2023). ABMS can capture complex, non-linear market dynamics and adaptive behaviors that traditional models might miss, particularly in modeling supply disruptions and their market impacts (Riddle et al., 2021).

4.3.2. Consumer behavior

Consumer behavior modeling through ABMS encounters several methodological challenges. Accurately representing social influence mechanisms requires constructing complex networks based on homophily principles, while capturing dynamic influence effects that vary across different contexts (Delcea et al., 2019; Scalco et al., 2019). The heterogeneity in consumer preferences and decision-making processes demands models that account for individual characteristics while considering spatial information and temporal dynamics (Dulam et al., 2021).

The integration of multiple behavioral factors presents significant complexity, as models must simultaneously account for personality, age, product prices, and various psychological theories (Liu et al., 2017; Scalco et al., 2019). Validation challenges persist, as agents in simulations often systematically differ from real consumer data due to factors like food waste not being accounted for in model elaborations (Dulam et al., 2021). The rich data requirements for creating realistic individual agents with distinct characteristics and rule sets pose another practical limitation (Sturley et al., 2018).

However, ABMS offers substantial opportunities for analyzing consumer behavior. This modeling approach enables comprehensive policy testing and intervention design, creating virtual laboratories for "what-if" approaches to policy evaluation (Dulam et al., 2021; Scalco et al., 2019). Models can reveal how social influence positively affects purchase intentions for eco-friendly products and how media exposure affects environmental attitudes (Delcea et al., 2019). ABMS excels at predicting unintended consequences, such as boomerang effects where social marketing campaigns produce opposite effects to those intended (Scalco et al., 2019). The methodology supports multi-context behavioral analysis, examining how campaigns can change consumption determinants in one context and affect members in another (Scalco et al., 2019).

4.3.3. Market penetration

Market penetration studies face challenges in modeling complex social influences, particularly in capturing shared consumption influences where consumers derive value from joint experiences (Delre et al., 2016). Homophily effects and network structure present methodological difficulties, as homophily may account for up to 50% of contagion processes, yet research examining aggregate market effects remains limited (Nejad et al., 2015). Consumer heterogeneity modeling requires representing diverse preferences and behaviors while maintaining computational tractability (Amini et al., 2012).

Validation proves challenging due to the heterogeneity of agents and emergence of new macro-level patterns from micro-level interactions (Noori & Tatari, 2016). Parameter uncertainty and deep uncertainty necessitate sophisticated approaches, such as Exploratory Modeling and Analysis, when decision-makers cannot agree on system components or predict plausible behaviors (Noori et al., 2016). Social network structure and influence quantification remain problematic, as determining appropriate network structures for specific markets and quantifying influence effects requires empirical grounding (Delre, Jager, & Janssen, 2007).

Despite these challenges, ABMS offers valuable opportunities for market penetration analysis. The integration of real-world network data provides stronger empirical grounding compared to theoretical network structures (Nejad et al., 2015). Comprehensive policy testing demonstrates how government subsidies combined with word-of-mouth effects can achieve significant market share targets (Noori & Tatari, 2016) Multi-criteria decision integration enables the incorporation of multiple decision factors, including costs, environmental impacts, and performance metrics (Noori & Tatari, 2016). Brand-level analysis capabilities allow for examination of disaggregated market analysis and competitive dynamics that traditional models cannot provide (Schramm et al., 2010).

4.3.4. Competition and pricing strategies

Competition and pricing strategy modeling faces significant complexity in representing strategic bidding behavior in competitive markets, particularly in balancing markets prone to strategic bidding due to limited providers (Poplavskaya et al., 2020). Learning algorithm selection and calibration present methodological challenges, as different algorithms produce varying results requiring careful parameter tuning

(Aliabadi et al., 2017). The complexity of multi-dimensional decision modeling emerges when contractors must consider multiple factors under bounded information and time constraints (Awwad et al., 2015).

Validation difficulties arise because actual strategies of market participants are typically not disclosed, forcing reliance on observable market outcomes rather than actual decision processes (Poplavskaya et al., 2020). Computational complexity increases substantially with the number of agents and decision variables, requiring hierarchical approaches to maintain tractability (Dehghanpour & Nehrir, 2017). Behavioral adaptation modeling presents challenges in capturing realistic adaptation over time, as pricing actions may not achieve the expected results due to changes in user behavior (Zheng et al., 2016).

Nevertheless, ABMS provides opportunities for competition and pricing analysis. The integration of advanced learning mechanisms enables more realistic strategic behavior modeling through reinforcement learning approaches (Poplavskaya et al., 2020). Market design optimization allows systematic evaluation of different combinations of pricing rules and market structures before implementation (Poplavskaya et al., 2020). Multi-objective optimization frameworks enable addressing competing objectives while maintaining system-wide constraints (Dehghanpour & Nehrir, 2017). Real-time adaptation and learning capabilities allow modeling of dynamic adaptation to market conditions (Awwad et al., 2015).

4.3.5. Financial market mechanisms and stability

Financial market modeling through ABMS encounters challenges in addressing deep uncertainty and non-linearity, particularly in climate-related financial risks that challenge conventional modeling approaches (Battiston et al., 2021). Financial network interconnectedness modeling requires representing complex risk transmission mechanisms through overlapping portfolios and funding networks (Bookstaber et al., 2018). Endogenous crisis generation presents difficulties in modeling how crises emerge from agent interactions rather than external shocks (Bookstaber et al., 2018).

The complexity of securitization and shadow banking systems requires sophisticated approaches to capture how financial innovations affect lending standards and systemic risk (Botta et al., 2021). Climate-financial system integration demands modeling complex feedback loops between environmental factors and financial stability (Lamperti et al., 2019). Hidden internal states of agents, such as sentiment and strategy types, must be inferred indirectly from market data, complicating validation and parameter estimation (Vidal-Tomás & Alfarano, 2020).

However, ABMS offers substantial opportunities for financial market analysis. Dynamic stress testing enhancement extends analysis from microprudential to macroprudential approaches by incorporating feedback mechanisms and network effects (Bookstaber et al., 2018). Climate-finance risk integration enables examination of both physical and transition risks through network modeling and dynamic evolutionary approaches (Battiston et al., 2021). Policy experimentation platforms allow testing of various interventions including progressive taxation and financial transaction taxes (Botta et al., 2021). Real-time crisis prediction capabilities emerge through tracking leading indicators such as non-performing loans (Botta et al., 2021).

4.3.6. Policy effect and regulatory impact

Policy-focused ABMS faces challenges in accurately capturing the complexity of human behavior under uncertainty, requiring careful integration of psychological and behavioral constructs into computational frameworks (Kashani et al., 2019). Model complexity and validation in policy contexts require balancing sophisticated representation with practical usability, often requiring extensive computational resources for reliable analysis (Pearce & Slade, 2018). Temporal scale and dynamic policy feedback loops create multi-temporal complexities where tactical and operational decisions occur at different frequencies (Van Heeswijk et al., 2019).

Agent heterogeneity and policy response variation present challenges in predicting aggregate outcomes when diverse agents respond differently to interventions based on varying motivations and capabilities (Vinogradov et al., 2020). Policy interaction effects and unintended consequences require modeling complex interactions between multiple instruments that can produce non-linear outcomes (Wu et al., 2018). Scale and aggregation issues demand careful consideration of which factors should be treated as exogenous versus endogenous (Klassert et al., 2015).

Despite these challenges, ABMS provides valuable opportunities for policy analysis. Policy scenario exploration enables comprehensive evaluation of multiple intervention approaches, as demonstrated through analysis of feed-in tariff schemes (Pearce & Slade, 2018). Real-time policy calibration supports adaptive management through continuous model refinement based on observed outcomes (Van Heeswijk et al., 2019). Multi-stakeholder impact assessment provides insights into how regulations affect different groups and how effects propagate through systems (Van Heeswijk et al., 2019). Behavioral policy design opportunities emerge through the incorporation of behavior-driven decision models that support nudging strategies (Moglia et al., 2018).

4.3.7. Innovation and market diffusion

Innovation diffusion modeling faces challenges in data collection and parameter calibration, particularly in low-resource settings where traditional survey methods may be inadequate (Pakravan & MacCarty, 2021). The integration of multiple behavioral theories requires effectively combining diverse frameworks, such as rational choice theory with psychological models, within single agent-based models (Pakravan & MacCarty, 2021). Social network modeling complexity emerges in capturing realistic network structures and determining appropriate parameters for degree centrality and update probabilities (Meles & Ryan, 2022).

Behavioral uncertainty quantification presents challenges in capturing and quantifying uncertainties related to the replication of agency and reality (Stavrakas et al., 2019). Network structure limitations appear in models' inability to reproduce high diffusion probabilities across distant peers during early lifecycle stages (Lengyel et al., 2020). Threshold distribution modeling requires accurately representing adoption thresholds while acknowledging their heterogeneous and difficult-to-observe nature (Shi et al., 2021).

However, ABMS offers significant opportunities for analyzing innovation diffusion. Policy-informed model development enables the testing of intervention scenarios before implementation, as well as the evaluation of grant programs, information campaigns, and regulatory changes (Meles & Ryan, 2022). The integration of economic and behavioral factors provides a more realistic adoption modeling approach by combining utility theory with behavioral psychology (Pakravan & MacCarty, 2021). Multi-level network integration captures diffusion dynamics through multiple network layers representing different connection types (Shi et al., 2021). Spatial-temporal analysis incorporates geographic and temporal dimensions, revealing features that traditional models miss (Lengyel et al., 2020).

4.3.8. Market vulnerability and crises

Market vulnerability analysis through ABMS encounters challenges in model validation and calibration complexity, requiring extensive Monte Carlo analyses to achieve robust results (Bookstaber et al., 2018). Network reconstruction and data limitations arise because interbank networks remain largely unobserved, forcing approximation methods that may not capture individual bank-level behaviors (Liu et al., 2020). Capturing dynamic network formation proves difficult as existing models may not adequately represent how fragility and shocks propagate in dynamic environments (Bookstaber et al., 2018).

Computational complexity and parameter sensitivity create practical limitations, as models require substantial computational resources and can be sensitive to specific parameter choices (Liu et al., 2020). Scale and heterogeneity management becomes challenging when representing large-scale systems like the entire U.S. banking system with over 10,000 institutions while maintaining computational tractability (Liu et al., 2020).

Despite these challenges, ABMS provides valuable opportunities for vulnerability analysis. Enhanced stress testing capabilities extend analysis to dynamic, macroprudential approaches that test how regulations impact network structures (Bookstaber et al., 2018). Endogenous network formation analysis examines how individual bank performance objectives impact contagion, revealing that endogenous models often show fewer failures than stationary models (Liu et al., 2020). Policy impact assessment enables quantification of banking crises and public bailout costs, demonstrating how macroprudential regulation can attenuate these costs (Lamperti et al., 2019). Multi-layered risk analysis captures interconnected relationships that cause reverberations across stressed financial systems (Bookstaber et al., 2018).

4.3.9. Market impact and volatility

Market impact and volatility modeling faces fundamental challenges in the trade-off between market stability and resilience, where policies effective in reducing volatility may prolong recovery times (Leal & Napoletano, 2019). Modeling complex trader interactions and feedback loops requires capturing contradictory mechanisms where high-frequency trading can be both destabilizing and stabilizing (Westphal & Sornette, 2020). Parameter sensitivity and calibration challenges emerge particularly when modeling sophisticated trading strategies with activation thresholds and pricing mechanisms (Leal & Napoletano, 2019).

Self-referential trading strategy effects create unique challenges where widespread adoption of predictive algorithms can destroy the patterns they seek to exploit (Westphal & Sornette, 2020). Model complexity and computational burden increase when capturing multifaceted interactions between climate variability, price volatility, and household decision-making (Wossen et al., 2018). Representing heterogeneous agent behavior under uncertainty requires modeling varying risk perceptions and coping mechanisms across different agent types (Sun et al., 2014).

However, ABMS offers opportunities for market impact analysis. Regulatory policy testing enables evaluation of circuit breaker designs, minimum resting times, and transaction taxes before implementation (Leal & Napoletano, 2019). Understanding emergent market properties allows study of phenomena like flash crashes that arise from trader interactions rather than external shocks (Leal & Napoletano, 2019). Bubble detection and prediction mechanisms can be tested in controlled environments to assess their market impact and effectiveness (Westphal & Sornette, 2020). Comprehensive impact assessment capabilities enable simultaneous evaluation of impacts on income, food security, and distributional effects across different market conditions (Wossen et al., 2018).

4.4. Discussion

The systematic review of ABMS applications across nine distinct decision areas in economic and financial markets reveals a complex landscape of methodological challenges and transformative opportunities. To provide a structured roadmap for future research, Table 2 categorizes these diverse issues into distinct strategic domains. This categorization offers a hierarchical perspective, distinguishing between immediate infrastructural and methodological prerequisites and long-term theoretical advancements.

While Table 2 outlines discrete challenges and their corresponding strategic solutions, the practical implementation of ABMS is often constrained by fundamental trade-offs that cut across these domains. To fully understand the landscape of ABMS applications, we must examine the current state, fundamental tensions, and future directions of ABMS in market analysis. The following subsections analyze these fundamental tensions and cross-cutting challenges in detail.

4.4.1. Fundamental tensions in ABMS implementation

Our analysis reveals three fundamental tensions that shape the application of ABMS across all decision areas, each presenting both constraints and opportunities for advancement.

4.4.1.1. The Complexity-Tractability Paradox. The most pervasive tension in ABMS applications is the trade-off between model realism and computational tractability. This paradox manifests differently across decision areas but consistently forces researchers to make difficult choices between capturing real-world complexity and maintaining analytical feasibility. In financial market stability models, researchers must balance representing sophisticated trading strategies with computational limits (Lussange et al., 2021; Poplavskaya et al., 2020), while consumer behavior models struggle to integrate multiple behavioral theories without becoming computationally prohibitive (Pakravan & MacCarty, 2021; Scalco et al., 2019). This tension is particularly acute in crisis and volatility modeling, where the very phenomena of interest—flash crashes, contagion cascades, and emergent market behaviors—arise from complex agent interactions that resist simplification (Bookstaber et al., 2018; Westphal & Sornette, 2020). The computational demands often force researchers to limit model scope or agent definition sophistication, potentially missing crucial dynamics that emerge only at scale or through intricate behavioral interactions.

However, this challenge also presents an opportunity for methodological innovation. The development of modular modeling frameworks that allow for scalable complexity could address this tension by enabling researchers to validate components independently while maintaining flexibility in model assembly (Lamperti et al., 2019). Advanced computational techniques, including parallel processing and machine learning integration, offer promising pathways for managing complexity without sacrificing insight (Dehghanpour & Nehrir, 2017).

4.4.1.2. The Validation-Innovation Dilemma. A second fundamental tension emerges between the need for empirical validation and the innovative potential of ABMS to explore unprecedented

Table 2. Strategic priorities, methodological challenges, and future directions in ABMS.

Strategic Domain	Key Challenges	Emerging Opportunities and Solutions
Methodological Rigor	**Validation & Verification**: Lack of standardized protocols; difficulty validating non-stationary dynamics against historical data.	**Hierarchical Validation**: Adoption of history-friendly, causal, and meso-level validation protocols to ensure structural validity.
	Calibration: "Curse of dimensionality" in parameter space; sensitivity to initial conditions.	**Automated Calibration**: Utilization of Bayesian estimation and black-box simulation-based inference.
Infrastructure	**Scalability**: Trade-offs between agent heterogeneity and computational feasibility.	**Advanced Computing**: Integration of cloud infrastructure, GPU acceleration, and distributed optimization schemes.
Data Integration	**Empirical Grounding**: Scarcity of micro-level behavioral data; privacy concerns.	**Real-time Assimilation**: Integration of unstructured big data (e.g., social media) and real-time market monitoring.
Theoretical Advancement	**Behavioral Specification**: The "wilderness of bounded rationality" and overfitting to historical regimes.	Adaptive Intelligence: Integration of Deep Reinforcement Learning and Evolutionary Game Theory for autonomous strategy adaptation.
	Generalizability: Balancing context-specific realism with generalizable economic principles.	**Middle-Range Theories**: Development of theoretical frameworks that identify invariant principles across specific market contexts.
Policy Application	**Interpretability**: Communicating complex, stochastic results to non-expert stakeholders.	**Participatory Modeling**: Engaging stakeholders via "digital twins" and scenario visualization tools.
	Systemic Risk: Capturing cross-sectoral spillovers (e.g., climate-finance loops).	**Integrated Assessment**: Multi-system modeling connecting financial stability with ecological and social dynamics.

scenarios. Traditional validation approaches, developed for equilibrium-based models, often prove inadequate for the non-stationary, path-dependent dynamics that ABMS excels at capturing (Awwad & Ammoury, 2019; Lorscheid et al., 2019). This creates a methodological catch: the very novelty that makes ABMS valuable for understanding market dynamics also makes it challenging to validate against historical patterns. This dilemma is particularly pronounced in policy analysis and regulatory impact assessment, where ABMS's ability to test unprecedented interventions is most valuable, yet validation against counterfactual scenarios remains impossible (Pearce & Slade, 2018; Wu et al., 2018). Similarly, in innovation diffusion and market penetration studies, models must predict adoption patterns for technologies that may not yet exist, which challenges traditional validation frameworks (Meles & Ryan, 2022; Stavrakas et al., 2019). The resolution of this tension requires developing new validation paradigms that embrace uncertainty and focus on causal mechanisms rather than predictive accuracy alone. Techniques such as structural validation, where model-generated causal relationships are compared with theoretical expectations and empirical patterns, offer promising alternatives to traditional forecast accuracy metrics (Fagiolo et al., 2004; Lamperti et al., 2019).

4.4.1.3. The Specificity-generalizability trade-off.

The third tension involves balancing model specificity needed for practical relevance with the generalizability required for scientific advancement. ABMS applications often achieve practical relevance through detailed representation of specific market contexts, institutional arrangements, and behavioral patterns (Van Heeswijk et al., 2019; Vinogradov et al., 2020). However, this specificity can limit the transferability of insights across contexts and markets.

This trade-off is evident across all decision areas. Financial market models calibrated to specific exchanges may not generalize to different market structures (Vidal-Tomás & Alfarano, 2020), while consumer behavior models developed for particular demographic groups may not apply broadly (Dulam et al., 2021). Policy analysis models face similar challenges when institutional contexts vary significantly across jurisdictions (Klassert et al., 2015).

Addressing this tension requires developing theoretical frameworks that identify invariant principles underlying specific applications. The emergence of "middle-range theories" that operate between high-level abstractions and context-specific details offers a promising approach for building cumulative knowledge while maintaining practical relevance (BenDor et al., 2009).

4.4.2. Cross-cutting methodological challenges

Beyond these fundamental tensions, several methodological challenges consistently emerge across decision areas, each requiring targeted solutions for ABMS to realize its full potential.

4.4.2.1. Parameter sensitivity and the curse of dimensionality.

The proliferation of parameters in ABMS models creates significant challenges for calibration and sensitivity analysis. Models often contain dozens or hundreds of parameters representing agent characteristics, behavioral rules, and interaction mechanisms (Aliabadi et al., 2017; Raberto et al., 2019). This high dimensionality makes comprehensive sensitivity analysis computationally prohibitive and creates risks of over-fitting to calibration data.

The challenge is compounded by the interdependent nature of parameters in agent-based systems, where changing one parameter can have cascading effects throughout the model. In financial market models, for instance, trader threshold parameters interact with network structure parameters to produce emergent market behaviors that cannot be predicted from the effects of individual parameters (Riccetti et al., 2018). Addressing this challenge requires developing systematic approaches to parameter reduction and hierarchical calibration. Techniques from machine learning, such as feature importance analysis and dimensional reduction methods, could be adapted for ABMS parameter analysis. Additionally, the development of metamodeling approaches that create simplified representations of complex ABMS models could enable more efficient exploration of parameter spaces (Poledna et al., 2023).

4.4.2.2. Behavioral rule specification and psychological realism.

The specification of realistic behavioral rules remains a central challenge across all ABMS applications. Most models still rely on oversimplified behavioral assumptions despite the availability of rich insights from behavioral economics and psychology (Giráldez-Cru et al., 2020; Kashani et al., 2019). The challenge lies not in the absence of behavioral knowledge but in translating psychological theories into computational rules that maintain both realism and tractability.

This challenge is particularly acute in consumer behavior and market penetration models, where social influence mechanisms, cognitive biases, and preference formation processes must be formalized mathematically (Delcea et al., 2019; Nejad et al., 2015). The temporal dynamics of behavioral change add additional complexity, as models must capture both immediate responses and long-term adaptation processes (Scalco et al., 2019). Progress in this area requires closer collaboration between computational modelers and behavioral scientists. The development of standardized libraries of validated behavioral modules could accelerate progress by providing tested building blocks for model construction. Additionally, the integration of experimental economics methods with ABMS could offer empirical foundations to behavioral rule specification (He et al., 2016).

4.4.2.3. Network dynamics and social structure. The modeling of social networks and their evolution presents persistent challenges across multiple decision areas. Static network representations fail to capture the dynamic nature of social relationships, while dynamic network models introduce additional complexity and computational burden (Delre, Jager, & Janssen, 2007; Shi et al., 2021). The challenge is compounded by the limited availability of longitudinal network data for validation.

In financial markets, network effects influence contagion patterns and the propagation of systemic risk, making accurate network representation crucial for stability analysis (Liu et al., 2020). Consumer behavior models similarly depend on social network structures to capture influence and diffusion processes (Lengyel et al., 2020). The feedback between network structure and agent behavior creates additional complexity, as networks both influence and are influenced by agent actions.

Addressing these challenges requires developing adaptive network models that capture both endogenous network formation and the co-evolution of network structure with agent behavior. The integration of real-world network data from social media and digital platforms presents opportunities for a more empirical foundation of network models (Nejad et al., 2015).

4.4.3. Emerging opportunities and future directions

Despite these challenges, our review identifies several transformative opportunities that position ABMS at the forefront of economic and financial analysis.

4.4.3.1. Integration with artificial intelligence and machine learning. The convergence of ABMS with artificial intelligence and machine learning presents unprecedented opportunities to advance market analysis and generate insights. Machine learning algorithms can enhance agent decision-making capabilities, enabling more sophisticated and adaptive behaviors that better reflect real-world learning and adaptation processes (Lussange et al., 2021; Poplavskaya et al., 2020). Deep reinforcement learning, in particular, offers promising approaches for modeling strategic behavior in complex market environments.While earlier literature predominantly relied on value-based methods like Q-learning, the field is increasingly adopting modern Actor-Critic architectures and Proximal Policy Optimization (PPO) algorithms. These approaches offer enhanced stability and sample efficiency, particularly in environments with continuous action spaces or complex competitive dynamics.

Recent literature exemplifies this shift across various economic domains. For instance, in the area of dynamic pricing, Liu et al. (2024) systematically evaluate Deep Reinforcement Learning (DRL) models, comparing PPO, Deep Deterministic Policy Gradient (DDPG), and Soft Actor-Critic (SAC). Their findings highlight that while PPO is computationally efficient, off-policy methods like SAC often provide superior stability and returns in scenarios with varying price elasticity.

Furthermore, hybrid frameworks integrating Evolutionary Game Theory with Deep Reinforcement Learning have emerged as powerful tools for adaptive strategy optimization. Cheng et al. (2024) demonstrate how such hybrid models can effectively capture real-time strategy adaptation in user-side electricity markets, offering a methodological template for modeling competitive dynamics in financial systems where agents must adapt to volatile environments.

Similarly, in macroeconomic simulation, Mi et al. (2023) introduced "TaxAI", a large-scale simulator that utilizes PPO and Multi-Agent PPO (MAPPO) to optimize fiscal policy among heterogeneous agents. The authors demonstrate that these modern DRL methods significantly outperform traditional genetic algorithms in complex social welfare tasks. Furthermore, in energy market production, Abdalla et al. (2023) apply an Actor-Critic framework to optimize steam injection rates and validate that Actor-Critic agents can handle non-linear system dynamics and minimize heat loss more effectively than conventional baselines.

Additionally, machine learning techniques can address traditional ABMS challenges such as parameter calibration and sensitivity analysis. Automated model discovery methods could identify optimal model structures and parameter combinations, while neural network metamodels could approximate complex ABMS dynamics for efficient scenario analysis (Dehghanpour & Nehrir, 2017).

The integration also enables the incorporation of unstructured data sources, such as news sentiment and social media content, into agent-based models. This capability is particularly valuable for financial market models, where sentiment and information flows significantly influence market dynamics (Vidal-Tomás & Alfarano, 2020).

4.4.3.2. Real-time market monitoring and policy support.

The increasing availability of real-time data streams opens opportunities for developing ABMS-based monitoring and early warning systems. Financial market models could provide real-time assessments of systemic risk and market stability, while consumer behavior models could track adoption dynamics for new products and services (Poledna et al., 2023). This capability is particularly valuable for policymakers who need timely insights into market developments.

Real-time ABMS applications require addressing significant technical challenges, including computational efficiency, data integration, and uncertainty quantification. However, successful implementation could transform how markets are monitored and regulated, enabling proactive rather than reactive policy interventions (Bookstaber et al., 2018).

4.4.3.3. Cross-domain integration and system-level analysis.

ABMS offers opportunities for integrating insights across traditionally separate domains of economic analysis. The ability to model multiple interacting markets simultaneously enables analysis of cross-market spillovers and systemic effects that cannot be captured by domain-specific models (Lamperti et al., 2019). Climate-finance integration exemplifies this potential, showing how environmental factors can be incorporated into financial stability analysis. This integrative capability is particularly valuable for understanding modern economic challenges that span multiple domains, such as digital transformation, sustainability transitions, and global supply chain disruptions. ABMS frameworks that can simultaneously model technological adoption, market competition, regulatory responses, and social dynamics offer comprehensive approaches to analyzing these complex phenomena (Riddle et al., 2021).

4.4.3.4. Participatory modeling and stakeholder engagement.

The transparent and intuitive nature of ABMS creates opportunities for participatory modeling approaches that engage stakeholders in the modeling process. This capability is particularly valuable for policy analysis, where stakeholder buy-in is crucial for successful implementation (Le Pira, Marcucci, Gatta, Ignaccolo, et al., 2017; Van Heeswijk et al., 2019). Participatory ABMS can facilitate dialogue among researchers, policymakers, and affected communities, leading to more robust and acceptable policy solutions.

The development of user-friendly modeling platforms and visualization tools could democratize access to ABMS capabilities, enabling broader participation in model development and analysis. This democratization could accelerate innovation by leveraging diverse perspectives and domain expertise.

4.4.4. Strategic priorities for ABMS advancement

Based on our comprehensive analysis, we identify several strategic priorities for advancing ABMS in economic and financial market analysis.

4.4.4.1. Methodological standardization and best practices.

The field would benefit significantly from the development of standardized methodological frameworks and best practices for ABMS implementation. This includes standardized approaches to model documentation, validation procedures, and the presentation of results. The development of common platforms and tools could facilitate collaboration and knowledge transfer across research groups and application domains (Lorscheid et al., 2019). Standardization should not suppress innovation but rather provide a foundation for systematic comparison and cumulative knowledge building. The establishment of benchmark models and validation datasets could enable systematic evaluation of methodological advances and facilitate replication studies.

4.4.4.2. Interdisciplinary collaboration and knowledge integration.

The complexity of modern market challenges requires interdisciplinary collaboration that brings together insights from economics, psychology, computer science, and domain-specific expertise. Successful ABMS applications increasingly require teams with diverse skill sets and theoretical backgrounds (Meles & Ryan, 2022; Pakravan & MacCarty, 2021).

Institutional support for interdisciplinary research and the development of cross-disciplinary training programs could accelerate progress in ABMS applications. The creation of research networks and collaborative platforms could facilitate knowledge sharing and joint project development across disciplinary boundaries.

4.4.4.3. Computational infrastructure and open science.

The computational demands of advanced ABMS applications require investment in computational infrastructure and the development of efficient modeling platforms. Cloud-based computing resources and specialized software frameworks could democratize access to high-performance computing capabilities (Awwad et al., 2015). Open science principles, including open-source modeling platforms and data sharing initiatives, could accelerate methodological development and facilitate reproducibility. The development of standardized data formats and model exchange protocols could enable broader collaboration and knowledge sharing within the ABMS community.

4.4.5. Implications for theory and practice

The insights from this review have significant implications for both theoretical development and practical application of ABMS in economic and financial markets.

4.4.5.1. Theoretical implications. ABMS challenges traditional economic theory by demonstrating the importance of heterogeneity, bounded rationality, and emergent phenomena in market dynamics. The ability to model non-equilibrium dynamics and path-dependent processes provides new insights into market behavior that cannot be captured by equilibrium-based theories (Fagiolo et al., 2004). This suggests a need for developing new theoretical frameworks that incorporate these insights while maintaining analytical tractability.

The emergence of markets as complex adaptive systems, demonstrated consistently across ABMS applications, suggests that market analysis should focus on understanding evolutionary processes, adaptation mechanisms, and emergent properties rather than static equilibrium states. This perspective has profound implications for how we conceptualize market efficiency, price formation, and policy intervention (BenDor et al., 2009).

4.4.5.2. Practical implications. For practitioners and policy makers, ABMS offers powerful tools for scenario analysis, stress testing, and policy evaluation. However, successful implementation requires understanding both the capabilities and limitations of these approaches. The emphasis on uncertainty quantification and scenario analysis, rather than point predictions, aligns with the inherent uncertainty in complex market systems (Noori et al., 2016). The ability to test interventions in virtual environments before real-world implementation provides valuable support for evidence-based policy making. However, this capability must be balanced with recognition of model limitations and the importance of combining ABMS insights with other analytical approaches and expert judgment (Wu et al., 2018).

In conclusion, ABMS represents an evolving methodology for understanding economic and financial markets. While significant challenges remain, the opportunities for advancing our understanding of market dynamics and supporting evidence-based decision-making are substantial. The future of ABMS in economic analysis lies in addressing fundamental methodological challenges while leveraging emerging technological capabilities to provide insights that traditional approaches cannot deliver.

5. Summary and future directions

5.1. Main findings

This systematic review examined the application of ABMS in economics and financial markets, identifying the transformative potential and persistent challenges of this methodological approach. Throughout our two-stage systematic review method, we identified and analyzed influential research spanning nine distinct decision areas: economic forecasting and market dynamics, consumer behavior, market penetration, competition and pricing strategies, financial market mechanisms and stability, policy effects and regulatory impact, innovation diffusion and market diffusion, market vulnerability and crises, and market impact and volatility.

Our analysis indicates that ABMS has established itself as a methodological approach for modeling complex market dynamics, with demonstrated capabilities in capturing heterogeneous agent behaviors, non-equilibrium dynamics, and emergent phenomena that traditional economic models often find challenging to represent (Dosi & Roventini, 2019; Farmer & Foley, 2009).

The applications across decision areas reveal several consistent contributions. ABMS enables bottom-up modeling approaches that connect individual-level decision making to aggregate market outcomes, as demonstrated in studies ranging from consumer behavior analysis (Scalco et al., 2019) to financial market stability research (Bookstaber et al., 2018). The methodology has shown particular value in policy analysis contexts where stakeholder heterogeneity and behavioral responses are critical factors, evidenced by applications in regulatory impact assessment (Van Heeswijk et al., 2019) and innovation diffusion analysis (Meles & Ryan, 2022). Additionally, ABMS has advanced the modeling of non-linear relationships and feedback loops in complex economic systems, particularly in areas such as financial network contagion (Liu et al., 2020) and market vulnerability analysis (Lamperti et al., 2019).

The methodological evolution from early theoretical applications to empirically grounded models demonstrates the field's ongoing development. The framework presented by Jamali and Lazarova-Molnar (2024) illustrates how data-driven approaches now complement theory-driven modeling, while studies such as Poledna et al. (2023) demonstrate the potential for ABMS to achieve forecasting capabilities comparable to traditional econometric approaches.

5.2. Trends and technological integration

Several trends are shaping the development of ABMS in economic applications. The transition from primarily theory-driven to data-driven modeling approaches represents a methodological shift, as evidenced by studies that successfully integrate empirical micro data for agent initialization and enable real-time tracking of economic time series (Hassan et al., 2010; Kavak et al., 2018). This development moves the field beyond stylized fact replication toward forecasting capabilities, as demonstrated by Poledna et al. (2023) in their macroeconomic forecasting application.

Artificial intelligence integration is another development area where studies are incorporating machine learning and reinforcement learning methods and techniques into agent decision-making processes, which shows potential for addressing behavioral modeling challenges (Lussange et al., 2021; Poplavskaya et al., 2020). These approaches enable agents to learn and adapt strategies based on environmental feedback and potentially address criticisms about predetermined behavioral rules that have been raised in the literature (Fagiolo et al., 2004).

Computational advances have expanded the scale and complexity of possible simulations. Improvement by computational infrastructure, including distributed computing approaches demonstrated by studies such as Dehghanpour and Nehrir (2017), has enabled large-scale simulations and more complex agent interactions. Cloud computing and improved processing capabilities have reduced technical barriers to implementing sophisticated ABMS applications (Abar et al., 2017).

The adoption of ABMS by policy institutions represents another notable trend. Central banks and financial institutions are increasingly utilizing ABMS for high-stakes decision-making. For instance, the Bank of England has explored ABMS for housing market risk assessment (Haldane & Turrell, 2018) and the Austrian government utilized the ABMS framework developed by Poledna et al. (2023) to forecast the economic impact of COVID-19 lockdown measures in real-time. The COVID-19 pandemic also provided evidence of ABMS utility in crisis scenarios, where behavioral dynamics significantly influence economic outcomes (Dulam et al., ,2021)

5.3. Challenges and research gaps

Despite developments in the field, several challenges remain that limit the broader adoption and reliability of ABMS in economic applications. Parameter sensitivity and calibration complexity continue to present difficulties in our review. Aliabadi et al. (2017) demonstrated the extensive computational requirements for comprehensive sensitivity analysis. In contrast, Poledna et al. (2023) acknowledged what they term the "wilderness of bounded rationality" problem, referring to concerns about the degrees of freedom in agent-based model parameterization.

Validation of agent-based models is another persistent challenge. The absence of standardized validation protocols comparable to those in traditional econometrics creates uncertainty about model reliability (Janssen & Ostrom, 2006). Studies consistently report difficulties in establishing model credibility, with researchers noting that validation is often "omitted or performed in a partial, ad-hoc manner" (Chen et al., 2012). The sensitivity of model outcomes to parameter specifications compounds these validation challenges (Raberto et al., 2019).

Computational constraints continue to impose tradeoffs between simulation scale and behavioral complexity. This limitation is particularly apparent when incorporating sophisticated artificial intelligence driven agent behaviors, where memory and processing requirements can become prohibitive for large-population simulations (Lussange et al., 2021). The challenge extends beyond mere computational power to include algorithmic efficiency and model design considerations.

Theoretical foundation gaps represent a fundamental challenge identified across the literature. ABMS application in economics and finance lacks unified theoretical frameworks comparable to optimization theory in traditional economics (Arthur, 2021). The development of general principles for bounded rationality and agent interaction remains an open research area, as highlighted by multiple reviewers who point to the absence of widely accepted theoretical foundations for agent behavior specification (Conte & Paolucci, 2014).

Data integration challenges create practical barriers to empirical grounding. Converting real-world data into model-compatible formats remains time-intensive and technically demanding (Jamali & Lazarova-Molnar, 2024). Compatibility issues between micro-level survey data and macro-level accounting systems, noted by studies such as Van Heeswijk et al. (2019), create implementation difficulties that extend beyond technical considerations to fundamental methodological questions.

Finally, it is important to acknowledge the limitations of this review article itself. Our methodology relied exclusively on the Scopus database. While Scopus offers the broadest interdisciplinary coverage suitable for ABMS, this single-source approach may have excluded niche working papers or specific economic studies indexed solely in databases like EconLit or Web of Science. Future reviews could address this by employing a multi-database search strategy to ensure exhaustive coverage of the economic literature.

5.4. Future research directions

Several research directions emerge as priorities for advancing ABMS in economic and finance market analysis applications based on the analysis of current applications and identified limitations. Enhanced validation methodologies represent a critical need, particularly the development of standardized protocols for model verification and validation. The emphasis on out-of-sample forecasting capability, as demonstrated by Poledna et al. (2023), suggests a pathway toward more rigorous validation standards. Research into robustness testing across different parameter ranges and market conditions would address sensitivity concerns raised throughout the literature.

Cross-domain integration offers opportunities for methodological advancement. Hybrid approaches that combine ABMS with other modeling methodologies, including system dynamics and traditional econometric approaches, could leverage complementary strengths while addressing individual methodological limitations (Liu et al., 2017; Riccetti et al., 2015). The integration of network analysis with ABMS, demonstrated in studies such as Liu et al. (2020), illustrates the potential for such cross-methodological approaches.

Real-time applications represent an expanding frontier, particularly for policy analysis and market monitoring. The development of frameworks for dynamic response to changing economic conditions, building on crisis modeling successes during COVID-19, could expand ABMS utility for operational decision support. Research into rolling horizon optimization schemes and real-time data integration would support these applications (Dehghanpour & Nehrir, 2017).

Theoretical development remains a fundamental research priority. The advancement of theoretical foundations for bounded rationality and multi-agent interactions could provide more principled approaches to model design and behavioral rule specification. The work by Schlüter et al. (2017) on mapping behavioral theories into agent-based model structures suggests pathways for this theoretical development.

Scalability research addresses ongoing computational limitations. Investigation into computational architectures and algorithmic approaches that enable large-scale simulations without sacrificing behavioral complexity represents both a technical and methodological challenge. The distributed optimization approaches demonstrated by Dehghanpour and Nehrir (2017) provide examples of potential solutions, though broader research into scalability remains necessary.

5.5. Implications for research and practice

The applications reviewed across nine decision areas suggest several implications for different stakeholder groups. For researchers, the field presents opportunities for methodological innovation, particularly in areas where traditional economic models face limitations in capturing heterogeneous behaviors and non-equilibrium dynamics. The integration of behavioral economics, network theory, and computational approaches demonstrated throughout this review creates opportunities for interdisciplinary collaboration (Battiston et al., 2021; Scalco et al., 2019).

For policymakers, ABMS provides analytical tools for evaluating policy interventions in complex systems where stakeholder heterogeneity and behavioral responses are critical factors. The scenario analysis capabilities demonstrated in studies such as Van Heeswijk et al. (2019) and Pearce and Slade (2018) support evidence-based policy design, particularly in contexts where traditional models may not adequately capture policy transmission mechanisms.

Financial institutions can employ ABMS applications in risk management, stress testing, and strategic planning. The financial market stability applications reviewed in this study, including work by Bookstaber et al. (2018) and Poledna et al. (2014), demonstrate practical value for understanding market dynamics and institutional interactions. The ability to model endogenous network formation and contagion effects provides capabilities that complement traditional risk management approaches.

However, successful implementation requires acknowledging the methodological challenges identified in this review. Organizations considering ABMS adoption should invest in appropriate computational infrastructure, develop internal expertise in model validation and sensitivity analysis, and maintain realistic expectations about model capabilities and limitations.

5.6. Concluding remarks

This systematic review documents the application of ABMS across diverse economic and financial contexts, explicitly addressing the three research questions presented in the Section 1.

Regarding RQ1 (Applications), our analysis of nine decision areas confirms that ABMS has matured beyond theoretical exploration into a robust tool for capturing heterogeneous agent behaviors and non-equilibrium dynamics. The evidence presented indicates that ABMS has achieved sufficient development to warrant consideration by researchers working on economic problems characterized by complex interactions, particularly where traditional equilibrium models struggle to represent emergent phenomena.

Regarding RQ2 (Challenges and Opportunities), we identified that while the methodology offers unique advantages, it faces persistent bottlenecks. Specifically, challenges in validation protocols, theoretical foundations, and computational scalability remain significant. Successful application currently requires careful attention to sensitivity analysis and a transparent acknowledgment of these methodological limitations.

Finally, regarding RQ3 (Future Evolution), this review highlights that the future of ABMS lies in the convergence with advanced technologies and empirical methods. The trajectory is moving toward empirically grounded, data-driven modeling and the integration of artificial intelligence, which promises to resolve current trade-offs between behavioral realism and computational efficiency. Importantly, the cross-domain integrations identified throughout this review suggest that ABMS will find its greatest value as a complement to, rather than a substitute for, traditional economic modeling approaches.

In conclusion, future progress will depend on systematic attention to these challenges. As computational capabilities expand and theoretical foundations solidify, ABMS is positioned to become a standard instrument for analyzing the adaptive, evolving nature of modern economies.

Note

1. http://www.crisis-economics.eu

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