Agent-Based Models and Multi-Agent Systems: A Comprehensive Review of Distinctions, Synergies and Applications

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The agent-based model (ABM) and multi-agent system (MAS) computational approaches have gained significant attention in various scientific disciplines. While these terms are sometimes used interchangeably, an ABM and an MAS share common principles, but they differ in their underlying philosophies, modeling approaches and applications. This review paper aims to elucidate the differences between the ABM and MAS approaches, highlighting their individual strengths and exploring the potential synergies. Understanding these distinctions is crucial for researchers and practitioners seeking to employ these approaches effectively in their respective fields.

Keywords: agent-based model; multi-agent system; agent behavior; modeling and simulation

1. Introduction

The world comprises a myriad of systems, each exhibiting unique characteristics and behaviors that dictate their functioning. Caws and Bertalanffy defined the system as a whole consisting of several parts/members [1, 2]. Systems are intricately interconnected entities and play vital roles across a spectrum of domains, spanning from the biological to the social and technological spheres. Systems can be classified based on various criteria. Kurtz and Snowden have developed the Cynefin framework to classify systems based on their complexity. This framework includes five domains, with four designated categories (chaotic, complex, complicated and simple), and a central fifth area referred to as the domain of disorder [3–5].

Simple systems are characterized by clear cause-and-effect relationships that are predictable, repeatable and often linear in nature. In contrast, complicated systems feature logical relationships between cause and effect, but they are not self-evident and therefore require

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analysis or expertise. Moving further along the complexity spectrum, complex systems exhibit emergent properties where cause and effect are not readily apparent, making outcomes unpredictable and nonlinear. Finally, chaotic systems are marked by high turbulence and lack clear cause-and-effect relationships [3, 5]. By delineating these complexities, we can gain not only a better understanding of their diverse natures but also the tools to effectively study, simulate and manage the behaviors of these systems in various fields of study and application.

Meanwhile, another classification can be taken into consideration, which distinguishes between natural and human-made systems. Natural systems are frequently characterized as complex systems due to their intricate structure, dynamic behavior and emergent properties [6]. These systems include fireflies, ant colonies, bird flocks, schools of fish, organizations, customer behavior, party competition [7], and the list is endless. However, human-made systems, such as computer systems or social organizations, are designed to meet specific objectives. In today's context, artificial intelligence (AI) is a significant component of many modern human-made systems, offering advanced capabilities in data analysis, decision-making, automation and problem solving.

In both the study of complex systems and the field of AI, the concept of agents emerges as a central and foundational principle [8]. In the context of complex systems, agents are the smallest unit of organization in the system capable of producing a given response for a specific stimulus. This stimulus/response behavior of an agent is governed by a few very simple rules [9]. The concept of an agent is indeed founded on a radical critique of classical AI, considering that both simple and complex activities, such as problem solving, establishing a diagnosis, coordinating actions or building systems, result from the interaction among relatively autonomous and independent entities, referred to as agents. These agents operate within communities, sometimes employing intricate modes of cooperation, conflict and competition to survive and perpetuate themselves. From these interactions emerge organized structures that, in turn, constrain and modify the behaviors of these agents [10].

The agent-based model (ABM) and multi-agent system (MAS) computational methodologies are based on the concept of agents. In an MAS, the focus is on numerous independent agents interacting within a defined environment, collectively working toward specific objectives or tasks. These agents possess different degrees of autonomy and intelligence, allowing them to make decisions and influence their surroundings. Conversely, an ABM is focused on simulating the behavior of individual agents and their interactions within a system to provide insights into emergent phenomena and to study and analyze various real-world phenomena. While an MAS and an ABM share common principles, they differ in their underlying philosophies, modeling approaches and applications.

This review paper aims to provide a comparative analysis of multi-agent systems and agent-based models, examining their similarities and differences. Through a critical review of literature, we aim to elucidate their strengths and limitations, offering guidance to researchers and practitioners in selecting appropriate modeling approaches for their specific research questions and objectives.

The rest of the paper is organized as follows: Section 2 discusses the core concept of agents. Section 3 focuses on multi-agent systems, highlighting their properties and applications in various domains. Section 4 provides an in-depth exploration of agent-based modeling, elucidating its features, advantages and applications. A comparative analysis between the computational approaches is presented in Section 5. Finally, the paper concludes with a synthesis of the findings and discussions presented.

2. Agent

There is no universally accepted definition of an agent. Various definitions exist in the literature, from concise to elaborate and rigorous ones. These definitions are heavily influenced by the field of agent technology, including AI, software engineering, cognitive science, computer science and engineering. Rather than enumerating and discussing numerous definitions, we present two definitions of an agent that appear to be broad and commonly accepted across different research communities [11].

The first definition proposed by Wooldridge and Jennings [12] characterizes an agent as a hardware- or (more usually) software-based computer system that enjoys several defining properties. These properties include autonomy, allowing agents to operate without the direct intervention of humans or others, and enabling some kind of control over their actions and internal state. Additionally, the concept of social ability involves agents interacting with other agents via some form of agent-communication language. Reactivity refers to the agent's capability to perceive its environment and respond promptly to changes that occur within it. Proactivity is another critical trait where agents do not simply act in response to their environment; they are able to exhibit goal-directed behavior by taking the initiative.

The second definition, as proposed by Ferber [13], defines an agent as a software or hardware entity (a process) situated in either a virtual or a real environment, possessing various attributes. This entity is capable of acting within an environment, driven by a set of tendencies (individual objectives, goals, drives, satisfaction/survival function). This entity possesses resources of its own and has only a partial representation of the environment. It can communicate directly or indirectly with other agents and may have the potential for self-reproduction. The autonomous behavior exhibited by the agent arises from its perceptions, representations and interactions with the world and other agents. Ferber emphasizes the significance of each term in this definition, elaborating that a physical entity refers to something that operates in the tangible world, like a robot, airplane or car. Conversely, a software component or computer module is considered a virtual entity since it lacks a physical presence.

Most authors agree that although there are multiple definitions of the term "agent," several properties can be pointed out (as outlined by Wooldridge and Jennings in 1995 [12], Franklin and Graesser in 1996 [14], Chaib-draain et al. in 2001 [15], Macal and North in 2005 [16], Epstein in 2006 [17] and Crooks in 2011 [18]). These properties may help us further classify agents in useful ways. Table 1 lists several of the properties mentioned.

Property	Meaning
Autonomous	Exercises control over its own actions without direct intervention from humans or other agents.
Heterogenous	Every agent is explicitly represented. These agents may differ from one another in myriad ways: by preferences, memories, decision rules, social network, locations and so forth, some or all of which may adapt or change endogenously over time.
Reactive Sensing and Acting	Responds in a timely fashion to changes in the environment and modifies its behavior when environmental conditions change.
Bounded Rationality	There are two components of this: bounded information and bounded computing power. Agents have neither global information nor infinite computational capacity. Although they are typically purposive, they are not global optimizers; they use simple rules based on local information.
Goal-Oriented Proactive/Purposeful	Does not simply react to the environment stimuli.
Temporally Continuous	Is a continuously running process.
Communicative Social Ability	Communicates with other agents, perhaps including humans.
Learning Adaptive	Changes its behavior based on its previous experience.

Property	Meaning
Mobile	Capability to change its physical or virtual position within its environment.
Flexible	Actions are not scripted.

Table 1. Computational agent properties [12, 14, 16–18].

Agents are classified based on various characteristics, functionalities and capabilities. They are commonly categorized according to their behavior, level of autonomy and purpose. Here is an overview of agent classification.

Combining autonomy, cooperation and learning characteristics, Nwana [19] categorized agents into seven types based on their architecture and function (see Figure 1(a)): (*i*) collaborative agents; (*ii*) interface agents; (*iii*) mobile agents; (*iv*) information agents; (*v*) reactive agents; (*vi*) hybrid agents; and (*vii*) intelligent agents.

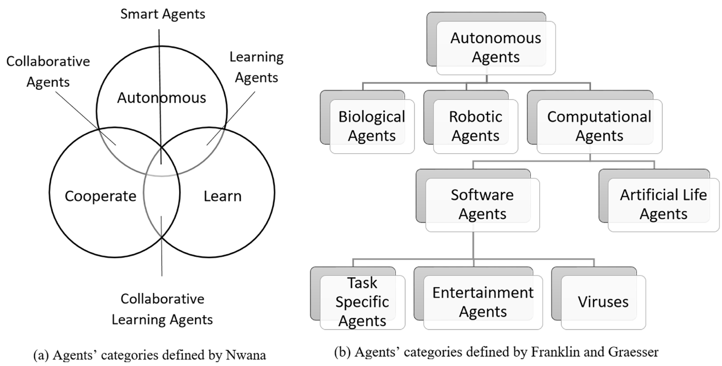

Figure 1. Agent taxonomies [14, 19].

Franklin and Graesser [14] proposed a taxonomy tree as represented in Figure 1(b), which divides the autonomous agents into three main groups: biological, robotic and computational, based on the distinction between animate organisms, artifacts and abstract concepts. Computational agents are subclassified into software agents and artificial life agents. At the class level, software agents are also subclassified into task-specific agents, entertainment agents and computer viruses. Some classification schemes for software agents are possible.

Brustoloni [20] suggests another classification that includes regulation, planning and adaptive agents. A regulation agent promptly responds to each sensory input and consistently knows its course of action without the need for planning or learning. Planning agents engage in planning using various methodologies. Brustoloni's adaptive agents not only engage in planning but also possess the ability to learn. A binary taxonomy approach can also be considered, including central or distributed control, planning or nonplanning, learning or nonlearning, mobile or nonmobile, communicative or noncommunicative.

Agents can additionally be categorized according to the application areas. These fields commonly encompass supply chain, consumer behavior, social networks, distributed computing, transportation and environmental studies. Agents have also been applied to several social and society fields, comprising population dynamics, epidemics outbreaks, biological applications, civilization development and military applications [21].

These taxonomies provide a comprehensive framework for understanding the diversity of agents, their functionalities and their roles across various application domains. In conclusion, agents represent a diverse and adaptable technology that is applied across a broad spectrum of fields. The classification and categorization of agents span various criteria, including their behavior, functionality and application domains.

Both MAS and ABM approaches fundamentally revolve around the concept of individual agents operating within a larger system. In an MAS, the emphasis is on multiple autonomous agents interacting within a given environment, contributing collectively to achieve specific goals or tasks. These agents possess varying degrees of autonomy and intelligence, allowing them to make decisions and influence their surroundings. On the other hand, the ABM focuses on simulating and understanding the behavior of individual agents and their interactions within a system, aiming to capture the emergent properties and dynamics that arise from these interactions. The common ground lies in recognizing that both the MAS and ABM approaches share a focus on the behavior and interactions of individual agents as fundamental determinants of overall system behavior.

3. Multi-Agent System

3.1 Background

For a long time, in the realm of AI and computational systems, programs have been considered as individualized entities capable of competing with humans in specific domains. Given the complexity of computer systems, it became necessary to break them down into “loosely coupled” modules, independent units with limited and perfectly controlled interactions. Thus, instead of dealing with a “machine,” we find a collection of interacting entities, each defined locally, without a detailed global view of all system actions. This way of approaching programs introduced new software engineering design methods and a change of perspective; we shifted from the concept of a program to that of organization.

The resolution of simple or complex problems thus became the result of interactions among relatively autonomous and independent entities, called agents, who work within communities using sometimes complex modes of cooperation, coordination, negotiation and competition to survive and perpetuate themselves. From these interactions emerge organized structures that, in turn, constrain and modify the behaviors of these agents [10]. The MAS can be traced back to the early days of research into distributed artificial intelligence (DAI) in the 1970s—indeed, to Carl Hewitt's concurrent Actor model [22]. In this model, Hewitt proposed the concept of a self-contained, interactive and concurrently executing object that he termed "actor." This object is an individual unit of computation that has its own state and behavior, and individuals can communicate with each other through message passing. The MAS gained formal recognition as a distinct research area in the 1980s and 1990s. Notable contributions by researchers like Les Gasser [23, 24], Michael Wooldridge and Nick Jennings [12, 25–27], Brahim Chaib-Draa et al. [15] and Jacques Ferber [10, 13] have shaped the theoretical foundations and practical applications of the MAS.

Before delving into a comprehensive exploration of MAS approaches, it is imperative to provide clear definitions for the term "multi-agent system." Regrettably, this task presents challenges because certain fundamental concepts do not possess universally accepted definitions [12]. Researchers and authors often tailor their definitions to the specific needs of their studies and projects, leading to a range of interpretations. Here we present two MAS definitions, which are considered quite general and have garnered broad acceptance across diverse research communities. As outlined by Ferber [10], an MAS is comprised of the following components:

- An environment E, that is, a space generally having a metric.
- A set of objects O, situated in the space, which can be perceived, created, destroyed and modified by the agent.
- A set of agents A, which are special objects ($A \subset O$); they are the active entities of the system.
- A set of relationships R that unite objects (and therefore agents) with each other.
- A set of operations Op, allowing agents of A to perceive, produce, consume, transform or manipulate objects of O.

- A set of operators Oe, charged with representing the application of these operations and the world's reaction to this attempt at modification, which will be called the laws of the universe.

According to Chaib-draa et al. [15], an MAS is designed and implemented ideally as a set of interacting agents, typically organized based on modes of cooperation, competition or coexistence. Additionally, he noted that an MAS is generally characterized by the following features: each agent has limited information or problem-solving abilities, thus each agent has a partial point of view, there is no global control of the MAS, the data is decentralized, and the calculation is asynchronous.

3.2 The Key Principles of Multi-Agent Systems

These definitions typically revolve around common properties. There is no official international or industry-wide agreement regarding a standardized list of properties for an MAS. The properties provided in the following are commonly recognized and discussed in the research community. The properties of an MAS can vary depending on the context and the specific goals of a research project or application (see Figure 2). Different researchers and practitioners may emphasize different properties based on their particular interests and the characteristics of the MAS they are studying. In the absence of an official agreement, researchers typically define and analyze properties based on the specific problem they are addressing. As a result, the properties of an MAS can be flexible and adaptable to suit the needs of individual research projects and applications.

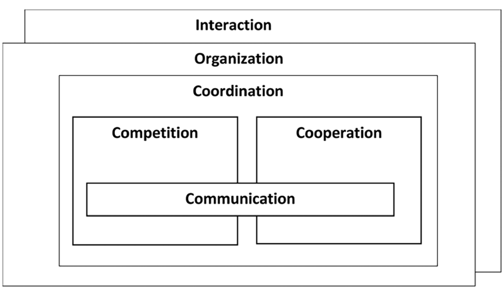

Figure 2. MAS properties.

Interactions. An MAS distinguishes itself from a collection of independent agents by the fact that agents interact with the aim of jointly accomplishing a task or achieving a specific goal [15]. These interactions are not only the result of actions performed by multiple agents simultaneously but also the essential element in the formation of social organizations [10]. Each agent can be characterized by three dimensions: their goals, their capabilities to perform and the resources at their disposal. The interactions among agents in an MAS are driven by the interdependence of agents along these three dimensions: their goals may be compatible or not, agents may desire resources possessed by others, and an agent X may possess a capacity necessary for agent Y to accomplish one of Y's action plans [15]. In the MAS realm, the benefit lies in incorporating sophisticated interaction patterns, enabling agents to coexist, compete or cooperate.

Organization. Organization, along with interaction, is one of the fundamental concepts in an MAS. Numerous definitions of the concept of organization have been put forth by different authors, including Morin [28] and Ferber [10, 29]. Common MAS organizational paradigms exist, and these paradigms enjoy broad recognition and utilization across diverse applications. Here are a few prevalent MAS organizational paradigms: hierarchical organization, holonic organization, team-based organization, coalitions, societies and self-organization [30]. In an MAS, there are numerous interrelations between agents, including task delegation, information transfer, commitments, action synchronizations and more. These interrelations are only possible within an organization, but conversely, organizations require the existence of these interrelations. Organizations therefore constitute both the support and the manner in which these interrelations are achieved [10].

Coordination. Coordination stands at the core of an MAS design. Rarely do agents operate in isolation; instead, agents often work in parallel to achieve a common goal. When multiple agents are employed to achieve a goal, there is a necessity to coordinate or synchronize the actions to ensure the stability of the system. Coordination between agents increases the chances of attaining an optimal global solution [30]. According to Nwana and Jennings [31], there are various reasons why agents need to coordinate: preventing chaos and anarchy, meeting global constraints, utilizing distributed resources, expertise and information, preventing conflicts between agents and improving the overall efficiency of the system [32]. In an MAS, coordinating the actions of different agents ensures system coherence. There are several coordination mechanisms, including organization, planning and synchronization [33].

Cooperation. Cooperation refers to the collaborative behavior and interactions among multiple agents to achieve shared goals or objectives. According to Ferber, cooperation involves agents working together, often by sharing information, resources or tasks, to collectively achieve better outcomes or solve complex problems [10]. However, agents can cooperate with no intention of doing so, and if this is the case, then the cooperation is emergent [34].

Competition. In contrast to cooperation, competition in an MAS pertains to situations where agents pursue their objectives independently and may even have conflicting interests. Competition can arise when agents have limited resources, compete for access to shared resources or have different goals that are not aligned.

Communication. Communication is one of the crucial components in an MAS that enables autonomous agents to interact, collaborate and achieve their objectives. Communication in an MAS can be mainly classified as two types. This is based on the architecture of the agent system and the type of information that is to be communicated between the agents [30]. The widely used approaches are local communication or message passing, where agents directly message each other, and network communication or Blackboard, where agents can collaboratively share data with each other using a central repository called Blackboard [35].

3.3 Application Areas

Various authors and researchers have proposed categorizations and classifications of the domains of MAS applications, depending on perspectives and research goals. Here is a broad suggestion provided by Chaib-Draa [15] that pursues two major objectives:

- The first concerns the theoretical and experimental analysis of the mechanisms that take place when several autonomous entities interact: they are placed within the cognitive sciences, social sciences and natural sciences to both model, explain and simulate natural phenomena and generate models of self-organization.
- The second focuses on the creation of distributed programs capable of accomplishing complex tasks via cooperation and interaction: they present themselves as a practice, a technique that aims to create complex computer systems based on the concepts of agent, communication, cooperation and coordination of actions.

According to Ferber [13], the main MAS applications are:

- *Problem solving*. An MAS offers an alternative to centralized problem solving, particularly effective when problems are distributed or when organizing problem solving among different agents proves more efficient.
- *Multi-agent simulation*. An MAS facilitates the creation of artificial universes for simulating and studying complex systems.
- *Construction of synthetic worlds*. The goal of an MAS is to develop societies of agents characterized by significant flexibility and adaptability, enabling them to function efficiently despite individual failures.

- *Collective robotics*. Utilized to coordinate multiple robots, an MAS is used where each subsystem has a specific goal, contributing to the achievement of a larger task. MAS approaches are valuable for coordinating different mobile robots in shared space.
- *Kinetic program design*. An MAS can also be viewed as a highly effective modular approach to programming.

4. Agent-Based Model

4.1 Background

Computer modeling and simulation (CMS) has emerged as a crucial research domain with practical applications in various industries and services. Given the complexity of most real-world systems, analytical methods often fall short, making numerical methods like simulation essential for studying system performance, understanding internal dynamics and exploring alternative scenarios [36]. Various modeling approaches exist, employing diverse representation formalisms and simulation methods. The selection of the most suitable modeling paradigm depends on the characteristics of the system being studied and the objectives of the simulation. Paradigms differ based on factors such as the representation of time (continuous or discrete) and the granularity of model elements (macroscopic or microscopic) [37]. The interest in incorporating the concept of agents into modeling and simulation primarily arises when dealing with the simulation of complex systems, which forms the foundation of the individual-based modeling (IBM) approach. The ABM is categorized within the broader spectrum of individual-based models. Within this category, closely related techniques such as cellular automata (CAs) and microsimulation are also prominent.

CAs are "discrete spatiotemporal dynamic systems governed by local rules" [38]. Despite their simplicity, CAs can exhibit extremely complex behavior and emergence. They are capable of modeling and simulating complex behavior with minimal rules. CAs consist of four key elements: a grid of cells with finite states, a neighborhood typically defined by the Moore (eight-cell) neighborhood, initial conditions for each cell and rules dictating state changes based on neighborhood properties. The model progresses by iteratively applying these rules to cells, followed by swapping the grid and repeating the process [39].

Schelling applied notions of CAs to study housing segregation patterns to create the first social agent-based simulation in which agents represent people and agent interactions represent a socially relevant process [40]. Schelling demonstrated that emergent patterns could arise that were not necessarily intended by individual agents, sparking significant interest and guiding development of agent-based modeling simulation (ABMS). Notably, Schelling's initial models were conducted without computer assistance, representing agents as coins moving on a checkerboard.

In 1987, Craig Reynolds developed the Boids model [41] that simulated flocking behavior, further demonstrating how local, individual rules could give rise to collective phenomena. Each simulated bird is implemented as an independent actor that navigates according to its local perception of the dynamic environment, using three simple rules that govern the behavior of individuals within the group. The ABM continues to evolve, from the Sugarscape model by Joshua M. Epstein and Robert Axtell in 1996 [42] to applications in epidemiology, economics and social sciences, expanding its reach and influence. Today, the ABM is applied in diverse fields, from modeling disease spread and financial markets to simulating complex societal behaviors, reflecting the ongoing evolution and significance of this modeling approach.

Agent-based modeling is known by many names. ABM (agent-based model), ABS (agent-based system), multi-agent system (MAS), multi-agent simulation (MAS), multi-agent-based simulation (MABS) or individual-based modeling (IBM), due to the wide range of applications that utilize the concept of agent as a fundamental element in simulation models [16, 21]. An ABM is a computational modeling technique that has gained significant popularity in various disciplines including economics, ecology, social sciences and epidemiology. It is particularly well suited for studying complex systems where individual agents interact with each other and their environment, giving rise to emergent behavior. The core idea of ABMS is that, instead of merely describing the overall global phenomenon, this phenomenon can rather be generated from the actions and interactions of agents. This bottom-up nature is the most important feature of ABMS [43]. Thus, the ABM is particularly suitable for analyzing complex adaptive systems and emergent phenomena [37, 44–46].

4.2 Concepts, Features and Advantages

An ABMS is a group of heterogeneous autonomous agents; each has its own objectives and is generally able to interact with the others and with its environment. In general, an ABM has three elements [16, 47–49]:

- A set of agents, their attributes and behaviors.
- A set of agent relationships and interaction methods: an underlying topology of connectivity defines how and with whom agents interact.
- Agent environment: agents interact with their environment in addition to other agents.

The ABM is a modeling approach that focuses on individual agents and their interactions to comprehend complex systems across various domains. It is characterized by several distinctive features [18, 50]:

- *Stochastic nature*. Involves randomness, leading to different outcomes across multiple runs.
- *Aggregative*. Predicts changes at a micro level and then combines these changes to understand larger-scale effects, following a bottom-up approach.
- *Emphasis on individual units*. An ABM analyzes individual agents that constitute the system, typically adaptive and capable of learning from experience.
- The ABM allows researchers to track the origins of specific decisions made by individual agents and analyze their decision-making processes.
- The ABM has the capacity to employ a vast number of parameters.
- The agents in an environment can be spatially explicit, which means that the agents have a location in geometric space, or they can be implicit, which means that their location in the environment is not relevant.
- In an ABM, the environment is shaped by the actions of the agents. In certain simulations, agents may even have the ability to alter the initial assumptions of the model.
- Capable of modeling nonlinear structures.

An ABM offers several advantages for simulating and understanding complex systems across various domains. These advantages can be summarized in three key statements:

0. An ABM captures emergent phenomena, which arise from interactions between individual entities. An ABM is suitable when:
   - Individual behavior is nonlinear.
   - There is a heterogeneous population of agents with varying rationality.
   - Agent interactions exhibit complex and heterogeneous topologies.
   - Agents display complex behaviors, including learning and adaptation.
1. An ABM provides a natural description of a system: an ABM is well-suited for describing and simulating systems composed of behavioral entities.
2. The ABM offers flexibility in several dimensions:
   - Simplifying the addition of more agents.

- Providing a natural framework for adjusting agent complexity, including behavior, rationality, learning, evolution and interaction rules.
- Allowing for changes in levels of description and aggregation [47].

4.3 Application Areas

The ABM is a versatile and powerful tool with a wide range of applications across diverse domains that is particularly valuable for simulating complex systems characterized by interactions between autonomous agents. The ABM allows us to model a wide spectrum of systems, from those in the distant past to those that have yet to emerge in the future. It is widely applied in fields such as social sciences, economics, supply chains, ecology, agriculture, crime, epidemiology, tourism, urban planning and more. Its flexibility and adaptability make it a powerful method for better understanding complex and dynamic systems and addressing real-world challenges. Researchers and practitioners continue to explore new avenues for applying the ABM, making it an indispensable and evolving modeling approach. Some example applications in these fields can be found in Table 2.

Application Area	Application Examples
Social Sciences	"Agent-Based Computational Models and Generative Social Science" (Epstein 1999) [51], *Simulation for the Social Scientist* (Gilbert and Troitzsch 2005) [52].
Economics	*Handbook of Computational Economics: Agent-Based Computational Economics* (Tesfatsion and Judd 2006) [53], *Agent-Based Modelling in Economics* (Hamill and Gilbert 2016) [54].
Supply Chains	"Agent-Based Modeling and Simulation for Supply Chain Risk Management: A Survey of the State-of-the-Art" (Chen, et al. 2013) [55], "An Agent-Based Model of Supply Chains with Dynamic Structures" (Li and Chan 2013) [56].
Ecology	*Individual-Based Modeling and Ecology* (Grimm and Railsback 2005) [57].
Agriculture	"A Review of Agent Based Modeling for Agricultural Policy Evaluation" (Kremmydas et al. 2018) [58].
Crime	"State of the Art in Agent-Based Modeling of Urban Crime: An Overview" (Groff et al. 2018) [59].
Epidemiology	"An Agent-Based Approach for Modeling Dynamics of Contagious Disease Spread" (Perez and Dragicevic 2009) [60], "An Agent-Based Modeling Approach Applied to the Spread of Cholera" (Crooks and Hailegiorgis 2014) [61].

Application Area	Application Examples
Tourism	"Agent-Based Modeling: A Powerful Tool for Tourism Researchers" (Nicholls et al. 2016) [62], "An Agent-Based Model of Tourism Destinations Choice" (Alvarez and Brida 2019) [63].
Urban	"Agent-Based Modeling in Urban and Architectural Research: A Brief Literature Review" (Chen 2012) [64], "Modelling Urban Expansion Using a Multi Agent–Based Model in the City of Changsha" (Zhang et al. 2010) [65].

Table 2. Agent-based modeling applications.

4.3.1 Example: Bird Flocking Model

The bird-flocking model, often referred to as the Boids "bird-oid" model, was introduced by Craig Reynolds in 1987 [41]. It is a classic example of an ABM used to simulate the flocking behavior of birds. Here is a detailed description of the model: Objective: To simulate and understand the collective behavior of a flock of birds, mimicking the behavior of each individual bird, with only a few simple rules.

Model Description

Agents (Boids). Agents in this model represent individual birds within a flock. Each Boid has its own position, velocity, orientation and simple rules governing its movement.

Environment. The environment is typically a two-dimensional space where the Boids move. It can be represented as a grid.

Rules

See Figure 3:

- Separation rule. Boids avoid collisions with their neighbors by maintaining a certain distance between them.
- Alignment rule. Boids align their velocity with that of nearby flockmates.
- Cohesion rule. Boids move toward the center of mass of their neighbors and attempt to stay close to nearby flockmates.

Interactions. Boids interact with their nearby neighbors based on the three aforementioned rules. They continuously adjust their positions and velocities according to these rules.

Emergent behavior. Through these simple local interactions, the model exhibits emergent behaviors, including flocking, coordinated movement and the avoidance of collisions. The collective motion of the flock arises from the individual Boids' adherence to basic rules.

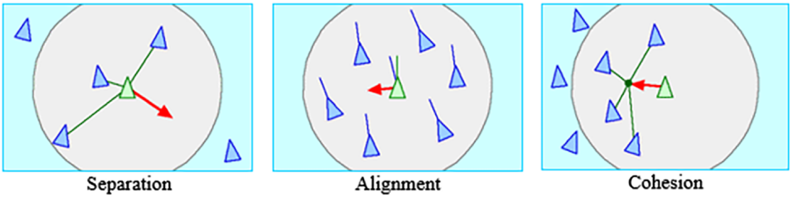

Figure 3. Bird-flocking model rules [41].

Model implementation. The Boids model has been implemented in various programming languages and environments. We can find open-source implementations and simulations of the Boids model in platforms like NetLogo (see Figure 4). This model serves as a fundamental example of how simple local interactions among agents can result in the emergence of complex and coordinated group behavior.

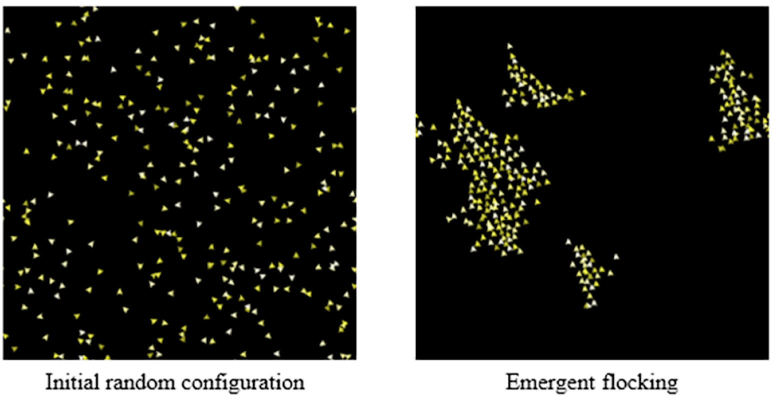

Figure 4. Simulation in Netlogo of bird-flocking model [41].

5. Comparison

The comparison between an MAS and an ABM delves into two distinct yet closely related concepts: the domain of complex systems and agent-based approaches. While both concepts revolve around the interactions and behaviors of autonomous agents, they address different aspects and serve diverse purposes. In this comparison, we explore the fundamental differences between an MAS as a system and an ABM as a modeling approach, shedding light on their unique contexts, analytical perspectives and areas of application.

An MAS refers to a system composed of multiple autonomous agents interacting with each other or with their environments to achieve specific goals. These agents can be individuals, software entities or robots, and they typically have their own goals, knowledge and capabilities. An MAS emphasizes the study of how agents interact and collaborate to solve complex problems or achieve tasks that may be challenging for individual agents alone. Conversely, the ABM serves as a modeling approach that replicates the actions and interactions of individual agents, aiming to uncover emergent behaviors resulting from these interactions. ABM applications span across various fields, including sociology, ecology and economics. An ABM meticulously scrutinizes the behaviors of individual agents to discern how their actions contribute to observable outcomes at the system level.

This comparative analysis explores the disparities between an MAS and an ABM, encompassing their definitions, areas of focus, objectives and tools (Table 3). By distinguishing an MAS as a system and an ABM as a modeling approach, we gain a deeper understanding of their distinct roles in the study of complex systems and agent-based phenomena, offering insights into their applications and implications in various domains.

Table 3 offers a simplified summary comparing MAS and ABM features across various aspects. These aspects include their focus, purpose, scale, emergence, complexity, agent behavior and properties, programming language and applications. By delineating these differences, a comparative analysis sheds light on the unique characteristics of each methodology and how they intersect within the broader context of studying complex systems and emergent phenomena.

Aspect	MAS	ABM
Focus	A system comprised of multiple autonomous agents interacting with each other or their environment.	Modeling methodology that simulates behaviors and interactions of individual agents.
Emphasis	Interaction, coordination, collaboration, competition and communication among agents.	Individual agent behavior and emergent system properties.
Purpose	Accomplishing a task, achieving a specific goal or solving complex problems.	Understanding a phenomenon or predicting the evolution of a system.
Scale	Macro level, studying overall system behavior and dynamics.	Micro level, focusing on agent interactions and behavior.

Table 3. (*continues*).

Aspect	MAS	ABM
Complexity	Arises from interactions among autonomous agents with diverse goals, knowledge, and capabilities.	Emerges from interactions among individual agents, each following simple rules.
Emergence	Refers to the spontaneous emergence of system-level behaviors or properties that are not explicitly programmed into the individual agents. Examples include self-organization, swarm intelligence and adaptive behavior, which arise from the interactions and coordination among agents.	Occurs when simple rules or behaviors at the individual agent level give rise to complex, system-level patterns or phenomena.
Agent Behavior	Agents interact and collaborate to achieve system objectives.	Agents have simple behavioral rules and interact locally among them at the micro scale.
Autonomy	Agents are autonomous entities with decision-making capabilities.	Individual agents are autonomous and make decisions based on simple rules.
Heterogeneity	Agents in the system may have diverse capabilities, behaviors or goals.	Can capture multiple types of agents, reflecting different attributes, behaviors or roles within the model.
Reactivity	Agents can react in real time to changes in the environment or actions of other agents.	Models reactive behavior where agents respond dynamically to changes in the environment or other agents.
Goal-Oriented	Agents have individual goals or objectives guiding their actions and decisions.	Focuses on modeling how individual agents pursue specific goals within the overall system.
Communication	Communication mechanisms enable agents to exchange information and coordinate actions.	May or may not explicitly model communication, depending on the specific application.

Table 3. (*continues*).

Aspect	MAS	ABM
Learning	Agents may have the ability to learn from experience, improving their behavior over time.	Learning mechanisms are incorporated to simulate how agents adapt their behavior based on their experiences.
Dynamic Environment	The environment in which agents operate is dynamic and may change over time.	Models a dynamic environment that influences the behavior and interactions of individual agents.
Parallelism	Agents can perform actions concurrently, enabling parallel processing and efficiency.	Utilizes parallel processing to represent simultaneous actions and interactions among individual agents.
Programming Languages	Often implemented using Java, Python or specific MAS libraries like JADE or AgentSpeak for MAS.	Typically implemented using languages such as Java, Python, NetLogo or specific ABM libraries like Repast, MASON or GAMA.
Applications	Distributed systems. Robotics, problem solving and program design.	Social sciences, ecology, economics, healthcare and tourism.

Table 3. MAS and ABM comparison.

6. Conclusion

In conclusion, the comparative analysis between a multi-agent system (MAS) and an agent-based model (ABM) provides valuable insights into their distinct yet interconnected nature. An MAS focuses on system-level behaviors resulting from interactions among autonomous agents, offering a macroscopic view of collective dynamics. In contrast, an ABM simulates individual agent behaviors to understand emergent properties, providing a micro-level perspective. The synthesis of findings from this study underscores the foundational principles that bind multi-agent systems and agent-based models, while simultaneously highlighting the nuances that distinguish them. The MAS, rooted in artificial intelligence (AI) and distributed systems, is characterized by its emphasis on explicit communication structures and formalized coordination mechanisms, making it applicable in domains such as robotics and decentralized control systems. Conversely, the ABM, originating in social sciences and economics, excels in capturing the emergence of complex phenomena.

In essence, the choice between them hinges on the intricacies and objectives of the system being studied. When the primary focus is on understanding how individual agents interact and influence the overall system behavior, an ABM may be more suitable. On the other hand, an MAS may be preferred when the emphasis is on designing and controlling autonomous agents within a system. An MAS allows for the development of systems with specific objectives, using coordination, cooperation or competition mechanisms among agents. Therefore, the choice between an MAS and an ABM depends on the modeling goals, level of detail required and the nature of the system under study.

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