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Review

Licence to Simulate: When Agent-Based Models Are More Fiction than Function †

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Abstract

Agent-based models are increasingly used to study supply chain systems due to their capacity to capture decentralised behaviour, heterogeneity, and emergent dynamics. However, the mere use of agent-based simulation platforms does not necessarily imply that the models fully exploit the agent-based paradigm. Although this concern, namely, the potential misuse of agent-based models, has been frequently raised in the literature, no previous study has precisely quantified how frequently this issue occurs, especially in the supply chain domain. To address this gap, a systematic review of 58 academic contributions was conducted to evaluate the extent to which agent-based models applied to supply chain contexts adhere to the fundamental principles of agent-based simulation. Specifically, the reviewed works were classified into two categories: *Green Flag* models, representing coherent and appropriate implementations of agent-based models, and *Red Flag* models, which fail to capture the essential characteristics of agent-based simulation. The classification was based on key discriminating factors such as the type and number of simulated entities or agents, the nature of agent interactions, and the incorporation of system-level dynamics. Further nuance is provided by two subtypes of Green Flag models: those featuring intelligent agents, and those based on responsive or reactive entities, which might generate emergent dynamics. Our results reveal that almost 64% of the analysed agent-based contributions lack key characteristics to justify the use of agent-based models. Hence, the paper also provides conceptual tools to aid in distinguishing between different agent-based approaches. In conclusion, the present work offers both a theoretical framework and a practical evaluation guide to support the development of future models and to foster critical analysis within the field.

Keywords: agent-based simulation; supply chain modelling; discrete event simulation; hybrid simulation; active and passive agents

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1. Introduction

In today's highly competitive and globalised economy, the effective design and efficient management of supply chains (SCs) have emerged as critical determinants of organisational success [1]. As markets grow increasingly interconnected and customer expectations continue to rise, the ability to effectively coordinate and optimise supply chain operations has emerged as a critical strategic advantage [2,3]. Also, over recent decades, SCs have undergone significant transformations, becoming more expansive and complex [4]. These changes have been driven by various factors, including the growing emphasis on environmental sustainability, which gained momentum in the last decade [5], and the recent wave of disruptions, ranging from the global pandemic to geopolitical tensions, which have underscored the fragility and interdependence of modern SCs [6,7].

To address these challenges, a wide array of tools and methodologies have been developed to support the design, planning, and optimisation of SCs. These include mathematical programming, heuristic and metaheuristic algorithms, digital twins, and machine learning techniques [8]. Among the available tools, simulation plays a central role and has proved to be particularly powerful, enabling researchers and practitioners to model dynamic behaviours, test scenarios, and evaluate performance under uncertainty without disrupting real-world operations [9]. Specifically, over the past decade, agent-based simulation (ABS) has been steadily gaining traction. This simulation paradigm is based on a collection of autonomous agents (such as suppliers, manufacturers, or customers) that operate independently, pursuing local objectives, but that can interact dynamically with other agents and the environment based on predefined rules [9]. This decentralised modelling approach is particularly well-suited for systems characterised by heterogeneity, distributed control, and non-linear interactions and it enables the emergence of complex system behaviours from simple interaction rules. For these reasons, the choice to simulate SCs, whose evolution and trend over time can be attributed to several different factors, is a particularly compelling and effective one [10].

However, in some cases, the models developed using the ABS paradigm do not explicitly require such an approach, as the dynamics of the simulated system do not necessitate the definition of active agents and could be more appropriately handled using simpler event-based systems or system dynamics models. In other words, while many models employ agents, it is not always clear whether the agent-based approach is necessary or merely a convenient design choice. Although this concern, namely, the potential misuse of agent-based models (ABMs), has been frequently raised in the literature (see for example [11–13]), there are no studies that have precisely quantified how frequently this issue occurs, especially in the SC domain. Even if the literature offers several comprehensive reviews and frameworks for ABS in SC contexts, none of them has systematically investigated whether and to what extent the use of ABS is essential to accurately represent the dynamics of a given SC model. It is therefore evident that a significant gap remains open in the literature in this regard.

To address this gap, the present paper pursues the following objectives: (i) to propose a set of guidelines for classifying the ABMs found in the literature; (ii) to categorise these models into two clusters, which we refer to as *Green Flag* and *Red Flag*, based on the necessity of using ABS; and (iii) to assess the extent to which existing ABMs fall into these categories, thereby evaluating whether ABS was essential or optional in each case.

The remainder of the paper is organised as follows. Section 2 provides the necessary background on simulation approaches within SC modelling. Section 3 outlines the key elements of our methodology, and the criteria used for classification. Section 4 introduces the analytical framework built around agent autonomy, interaction, and system evolution. Section 5 offers illustrative examples to clarify the application of this framework. Section 6 presents and discusses the main findings. Finally, Section 7 reports a summary of key insights and suggestions for future developments.

2. Background

Global and complex SCs, with both their strengths and weaknesses, are the network that drive economic systems [14,15]. The traditional economic focus of supply chain management (SCM) has broadened to also encompass environmental and social sustainability considerations within inter-organisational business systems [16]. Environmental influences and social factors modify SC systems, which in turn "react" or "adapt" to these socio-environmental changes. Therefore, the overall sustainability of economic systems ends up being dependent upon the complex interplay of SCs on several dimensions from the microscopic (intra-organisational) to the mesoscopic (inter-organisational) and macroscopic (industry—or sector wide aggregate) levels [17]. These complex interactions have long led researchers to look at supply networks as complex and adaptive systems [18]. For these reasons, simulation methods offer several advantages over other formal modelling approaches, such as multi-criteria decision making and mathematical programming, as effective and practical analytical tools for supply chain design and optimisation [19,20].

Several simulation approaches are available, each with distinct characteristics and preferred applications. Monte Carlo simulation is widely used for probabilistic analysis and risk assessment by generating random samples to model uncertainty [21]. Discrete event simulation (DES) focuses on systems where state changes occur at discrete points in time, making it suitable for modelling queuing systems and logistics operations [22]. System dynamics (SD) captures feedback loops and time delays in complex systems, often at an aggregate level [23].

In SCM research, these methods have been used to study different problems, such as identification and control of inventory levels, cost management, SC network design and facility location, and, notably, coordination mechanisms in the context of SC dynamics [24]. Readers can refer to [25] for a general review on discrete event simulation and system dynamics implementations in the SC domain, and to [26,27] for a comprehensive analysis of the development of multiagent systems in SC applications.

However, when modelling an SC as a collection of autonomous members that interact with and influence each other, learn from their experiences, and adapt their behaviours to be better suited to their environment, and when the objective is to study patterns, structures, and behaviours emerging through the agent interactions, ABS (often also labelled as multiagent system approach or multiagent simulation) is a primary modelling solution to cope with this kind of complexity [28]. In ABS, in fact, the core modelling element is the agent and its associated behaviours, which influence not only its own actions but also those of other agents and the environment [29,30]. More precisely, indeed, a typical agent-based model consists of three elements [31]: (i) a set of agents with their attributes and behaviours; (ii) a set of agent relationships and methods of interaction (how and with whom agents interact); and (iii) the agents' environment.

Even if there is no universally accepted definition of agents in the literature, the property of *autonomy* appears to be their most important defining feature. Therefore, agents should exhibit specific behaviours and be equipped with dedicated decision-making mechanisms, enabling them to make autonomous decisions in response to the situations they encounter, without relying on external control [31]. In that regard, agents could be active, with their actions aiming to achieve their internal goals, or passive, reacting to other agents and the environment. Agents' actions may be a direct intervention, a communication with other agents, or further reasoning. Moreover, agents possess mechanisms that adapt their behaviours, at a single and collective level, in response to accumulated experiences or learning by leveraging some form of memory [32,33]. In the case of learning, theories of learning become important and machine learning algorithms may be leveraged for recognising patterns in data [34].

Modelling agent relationships and interactions involves defining how agents are connected (i.e., the model's topology) and specifying the dynamics that govern their interactions [29]. In agent-based systems, by nature decentralised, each agent typically has access only to local information, which is acquired through interactions with neighbouring agents. An agent's neighbourhood can be represented as a network of nodes (agents) and links (relationships), and agents within a model may interact according to one or multiple topological structures.

In ABMs, the environment plays a crucial role as it may constrain agent actions in contending for space, acquiring resources, and so on [30]. The environment may simply provide the agent with information about its spatial location with respect to the other agents or with a richer set of geographic information. However, more sophisticated environmental models can be used to model the agents' environment to provide point location-specific data [31]. It is worth highlighting here that many of these applications involve hybrid simulation, that is a modelling approach that combines two or more techniques [35].

Since its origins, agent-based modelling has seen a variety of applications over a wide range of disciplines from physical sciences to social science and from biology to business and finance. ABMs have had many applications in the SC domain, and several authors have tried to systematise these applications in appropriate literature reviews. As ref. [36] points out in a synthetic, but very optimistic, way, the next generation of ABMs in SCM will be all of the following: (i) distributed; (ii) dynamic; (iii) intelligent; (iv) integrated; (v) responsive; (vi) reactive; (vii) cooperative; (viii) interactive; (ix) anytime; (x) complete; (xi) reconfigurable; (xii) general; (xiii) adaptable; and (xiv) backwards compatible.

Ref. [11] introduced a service-orientated framework for collaborative SCs, and it included practical applications and case studies that demonstrated the effectiveness of the proposed framework. Similarly, ref. [32] proposed a framework integrating ABS with simulation-based optimisation, thus allowing for a more dynamic and realistic representation of SC entities. This framework also emphasised how individual agents pursue their local objectives while also interacting with one another to achieve broader, holistic goals. Furthermore, ref. [37] provided a state-of-the-art survey on ABS for risk management in SCs, and this classification helps in understanding the various approaches and methodologies used in the field. The review in [33] offered a multi-level classification of ABS applications in logistics and SC research. It introduced a multi-level classification framework to systematically categorise the reviewed publications, and it helped to understand the various applications and issues related to ABS. Also, the research highlighted the different behaviours and capabilities of agents in ABS, such as their ability to learn and adapt, and it also assessed the maturity of various ABS applications, categorising them from conceptual proposals to field experiments. Lastly, other reviews investigated the contribution of ABS to SCs in various industry sectors, such as the relevant case of agri-food [14,38]. As for this literature review, to the best of the authors' knowledge, no previous study has explicitly addressed the issue of evaluating the proper use of the ABS approach, especially in the SC domain.

3. Method

The dataset underpinning this study was developed through a structured process that combined insights from prior research with an updated literature review, ensuring both continuity and comprehensiveness. The specific methodology is outlined in the following subsections.

3.1. Dataset Construction

The dataset was built by systematically applying the following steps.

1. *Prior Research*. The first input originates from the dataset used in our previous review [39], which consisted of 25 articles.
2. *Updated Search*. The second source was obtained by extending the original query, to broaden the covered period up to the end of 2024. This update resulted in 85 additional contributions.
3. *Dataset Refining*. The combined pool of 110 articles was then refined to ensure the quality and robustness of the analysis. Specifically, we decided to include only works published in peer-reviewed scientific journals, which are generally subject to stricter review standards, ensuring higher quality. Moreover, due to the greater space typically allowed in journal publications, the models and methodologies are usually described in more detail and with greater clarity. This level of detail is essential for applying the classification framework introduced in the following section. Brief or superficial descriptions, which are more common in conference papers, would not provide sufficient information to support a robust and reliable classification process. This exclusion criterion led to the removal of 49 articles from the initial dataset.
4. *In-Depth Analysis*. Each of the remaining articles was examined in depth to analyse the structure and substance of the simulation models, with a particular focus on agent behaviours and modelling choices. During this phase, three additional articles were removed as they addressed operations modelling rather than SC systems. The final dataset comprises 58 peer-reviewed journal articles, each one subjected to a systematic classification. The classification framework and methodology are outlined in the following section.

3.2. Classification Parameters

In this study, we systematically examined all the contributions included in the dataset, with the aim of capturing and comparing the core characteristics of each ABM across a set of defined analytical dimensions. This structured approach enabled a consistent and replicable evaluation process across all the models considered. Table 1 summarises the five descriptive parameters extracted from the analysis of each article: the model's context and objectives, the justification for adopting agent-based simulation, the types of simulated entities, the nature of the interactions, and the presence of system dynamics.

Table 1. Overview of applied classification criteria.

Parameter	Description
Context and Objectives	The application domain and the specific goals for which the ABM was developed (e.g., decision support, policy testing, behavioural exploration).
Justification for ABS	The rationale provided by the authors for adopting an agent-based approach, including reference to complexity, decentralisation, or adaptiveness.
Simulation Objects	The entities modelled as agents in the simulation (e.g., firms, consumers, logistics nodes), including their role and level of autonomy.
System Evolution over Time	Evidence of system-level evolution over time, driven by agent behaviour and interaction; includes structural shifts, convergence, or emergent patterns.
Type of Interactions	The presence and nature of interactions among agents: whether agents influence each other explicitly (directly) or through shared environmental variables (indirectly).

As summarised in Table 1, our analysis considered a range of model features, including domain context, modelling rationale, agent types, interaction mechanisms, and the presence of system-level dynamics. The first three parameters are descriptive in nature, while the final two are more technical. These latter dimensions enabled us to distinguish between models that fully exploit the agent-based paradigm and those that adopt agent-based elements in ways that could have been equally reproduced through conventional DES or SD logic. The former are classified as Green Flag models, while the latter fall under the Red Flag category.

In this regard, we recall that, as clearly stated in Section 1, this distinction is not intended as a critique of the models themselves, but rather as a neutral assessment of whether the agent-based approach was applied in a conceptually appropriate and technically justified manner. It is a classification based on the appropriateness or the adequacy of the ABS to the reproduced SC and does not depend, in any way, on either the complexity or on the quality of the obtained results. Indeed, we believe that, even if ABS is not strictly requested to soundly reproduce a supply chain, the result remains valid, but the work could have been streamlined. For example, if there are no interaction effects and no evolved agents, the agents are essentially just reacting to stimuli, which are, in fact, discrete events. In this case, they become functionally equivalent to DES objects, and the core idea of system evolution is lost. In such cases, the use of ABS makes the model more difficult to interpret and makes it harder to convey the actual objective. One modelling approach leads the reader to expect insights into system dynamics, while the other focuses on global system performance, without emphasising any evolutionary aspects.

In the following section, we examine each of these components in greater depth. We define the conceptual boundaries that differentiate operational flows from meaningful interactions, explain the conditions under which system evolution is considered significant, and articulate our rationale for classifying a model as Green or Red Flag based on these dimensions.

4. Guidelines for the Interpretation of the Classification Method

In this section, we articulate the theoretical and operational rationale underpinning our classification method. While in [39] we introduced a distinction between active and passive agents, we now refine and expand this evaluation using a triadic structure. This includes agent autonomy [31], interaction dynamics [29], and system evolution [40], three pillars that we consider essential for determining whether a model meaningfully leverages the agent-based paradigm. Collectively, the three dimensions provide a coherent evaluative framework that informs, and ultimately justifies, the Green/Red Flag classification introduced in the subsequent section. It is also important to note that the classification criteria used to label the analysed models as Green or Red Flag are not novel; rather, they reflect the fundamental characteristics commonly used in the literature to define agent-based models. This choice was a deliberate and strategic decision that we made based on two main considerations. First, we aimed to rely on reference criteria that are widely recognised and consolidated in the literature to ensure both clarity and methodological soundness. Second, we sought to strike a balance between two competing goals: increasing the granularity of the analysis by introducing more specific and detailed criteria related to model structure and behaviour versus preserving the interpretability and practical feasibility of the classification. Indeed, pushing for higher specificity would have significantly reduced the robustness of the results or, in some cases, made the classification process unmanageable. Overall, the key contribution and novelty of our work lies in the rigorous formalisation of when ABS is necessary and soundly used, and not in any technical innovation.

4.1. Degree of Agent Decision-Making Autonomy

We use the term active agent to refer to an autonomous object that can make independent decisions, adapt over time, and interact meaningfully with other agents in the surrounding environment. These agents are dynamic, heterogeneous, and capable of both initiating and responding to stimuli. For the agent to be considered *active*, the answer to this question must be affirmative: "*Does the agent's behaviour evolve over time in response to the environment or the actions of other agents?*"

This concept is illustrated in Figure 1, which conveys the core idea of an active agent whose behaviour is both dynamic and guided by goal-orientated reasoning, formally defined through a utility function. Conversely, a passive agent operates in a deterministic way and although its responses may vary in terms of quantity or timing (e.g., producing or ordering more), the underlying decision-making approaches remain fixed and predictable. Such actions occur solely in response to external stimuli, without genuine adaptation or learning.

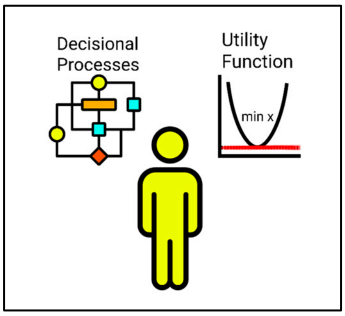


Figure 1. Key features of an active agent.

4.2. Nature of Inter-Agent Interactions

Before exploring the interaction-related criteria of the classification framework, we begin by clarifying the distinction between what we refer to as "mere operational flows" and "genuine inter-agent interactions". We then explain why the presence of inter-agent interaction is essential for a model to fully exploit ABM potential.

4.2.1. Mere Operational Flows vs. Agents' Interactions and Responsiveness

We use the term operational flows in an SC to refer to mechanical exchanges (e.g., delivery of goods, issuance of orders, or inventory movements) that occur regardless of agent cognition, intention, or responsiveness. These flows are embedded within the environment or programmed as fixed procedures, i.e., they are just structural mechanics rather than meaningful social or economic interactions among the agents. For instance, if a "consumer agent" issues a purchase order to a "producer agent" and the producer responds by simply executing a predefined routine, no true interaction is taking place. Interaction, instead, implies an active response triggered by the behaviour of other agents that not only operate within the same environment but actively perceive and respond to one another's behaviours. A possible genuine interaction is that of a producer that readjusts its operations (e.g., by increasing batch size, reallocating resources, etc.) as a consequence of the observed consumer demand. In light of this, in our classification, purely operational flows were not considered as real inter-agent interactions.

4.2.2. Direct Interactions

Agent interactions can be categorised as either direct or indirect. Direct interactions include negotiation, dynamic adaptation to the actions of others, and responses based on the observed state of other agents. These interactions are characterised by a fundamental question: "*Is there a direct exchange of material or information between two or more distinct agents, driven by their utility functions or procedural logic, which produces a tangible effect on at least one of them?*" A graphical exemplification of this concept is provided by Figure 2, where each node corresponds to a geographic area populated by consumer agents exhibiting distinct behaviours. Within each node, the agents interact directly with one another through decision-driven exchanges, depicted here as dialogue bubbles.

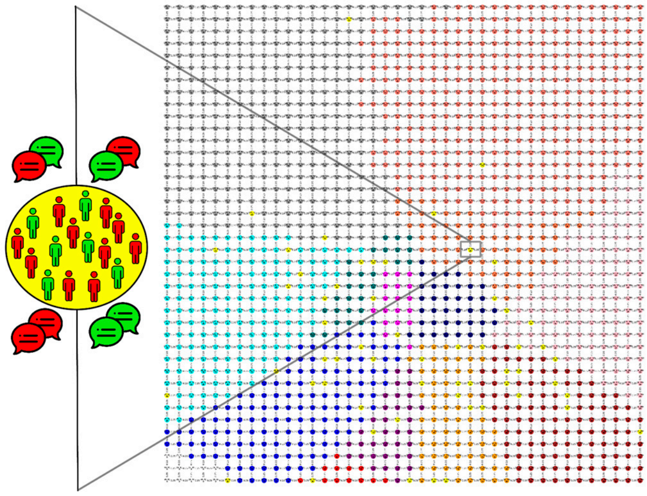


Figure 2. An example of direct interactions, based on peer dialogue and internal rules.

The agents communicate, react to peer influence and/or influence, and adjust their own decisions based on the attitudes, signals, or states of other agents in the same area. As a practical example, consider a grid representing an urban area in which a logistics operator is responsible for waste collection. Green agents represent virtuous citizens who sort their waste and dispose of it properly, whereas red agents represent those who only engage in unsorted waste disposal. In this scenario each citizen observes the behaviour of his or her neighbours and communicates with them (red and green clouds to represent different combination of interactions), potentially readapting, either positively or negatively, his or her behaviour, as a result of these interactions.

4.2.3. Indirect Interactions

An indirect interaction occurs when the action of one agent influences the decision making of another without explicit communication or targeted behaviour. In these cases, agents may be unaware of each other's presence, yet their decisions are shaped by shared environmental state variables, emergent collective dynamics, or feedback mechanisms operating at the system level. Therefore, the influence is mediated through the environment, rather than occurring via deliberate inter-agent messaging or mutual recognition. In terms of SC modelling, these interactions are particularly relevant where agents respond to emergent global signals, such as price shifts, congestion, stock levels, or regional scarcity. To sum up, the defining feature of indirect interactions can be captured by the following question: "*Is there an indirect flow of material or information between two or more different agents, based on their decision rules or utility function, that is conveyed by a third (mostly collective) entity, such as external environmental conditions or system-level variables?*" This is exemplified in Figure 3, which extends the scenario depicted in Figure 2. Agents within each node have already interacted directly, and this has led to the emergence of a predominant behavioural pattern (e.g., red or green). Once established, this dominance triggers a system-level propagation effect (represented by colour-coded concentric ripples) that influences the surrounding nodes, without requiring further direct inter-agent communication.

Returning to the example of waste disposal, the external or "third entity" that influences citizens' behaviour can either be the surrounding environment (e.g., overflowing bins, a general perception of neglect and decay, lack of cleanliness, etc.) or regulatory authorities (such as municipalities or regional governments), which may introduce incentives or penalties informed by the historical average behaviour of citizens.

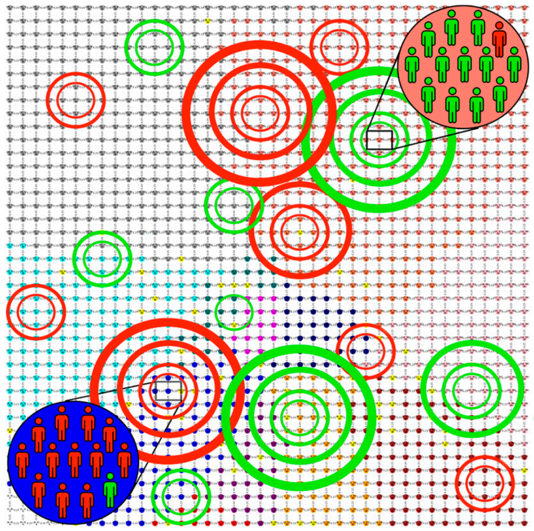


Figure 3. An example of indirect interactions triggered by predominant behavioural patterns.

4.3. System Evolution over Time

Another key feature of an ABM, typical but not limited to the models involving active agents (see Section 4.1), is the ability to generate system-level evolution over time. Unlike models in which the outcomes are predefined or merely the result of aggregated parameters, ABMs enable emergent phenomena to arise from decentralised decision making, local interactions, and dynamic feedback mechanisms This evolution is not externally imposed but emerges endogenously from the interplay of agent behaviours: as agents interact, adapt, and respond to both peers and environmental stimuli, the system progressively evolves. Over time, these micro-level processes give rise to macro-level patterns, structural transformations, and shifts in dominant behavioural regimes, which collectively characterise the systemic reconfiguration of the simulated environment. This principle is exemplified in Figure 4, which depicts a simplified scenario in which the system evolves from an initially mixed configuration (time t) to a more homogeneous behavioural state (time $t + n$). In this case, the agents are companies competing in the same market niche and based on their strategic decisions and operative actions, market conditions rapidly evolve from an initial state of oligopoly to one of monopoly.

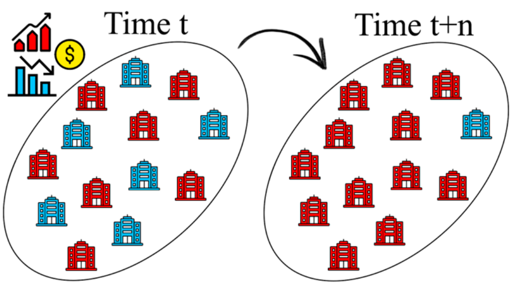


Figure 4. An example of system evolution, driven by market competition over time.

It is important to note that systemic evolution is not confined to ABMs involving active agents. As further discussed in the next section, under specific conditions, even models composed solely of passive agents may display non-trivial and unforeseen dynamics. In any event, this type of evolution cannot be traced back to a single agent's action or to an externally defined rule: it is not encoded in advance in the model but rather emerges unpredictably as the result of recursive interactions and adaptation within the system.

5. Green and Red Flag Models

As anticipated in the previous sections, from this point onward, the articles that meet our criteria for an appropriate and coherent use of agent-base paradigm in the context of SC modelling will be labelled as *Green Flag*, while those that do not will be labelled as *Red Flag*. To support this classification, we developed a simple, yet robust scheme grounded in the fundamental characteristics of agents introduced in Section 4. Its main characteristics are discussed in the following subsections.

5.1. The Green Flag–Red Flag Categorisation Scheme

The framework is intentionally designed to be both generic and easy to apply, making it suitable for use beyond the SC domain. Its main structure is exemplified in Table 2. As can be seen, the baseline requirement for a model to be labelled as Green Flag is criterion (i), that the model includes interaction among agents, whether direct or indirect. Without interactions, in fact, agents behave in isolation, and the system cannot exhibit meaningful emergent behaviour. Provided this condition is met, the model will be classified as Green Flag if at least one of the following criteria is satisfied: (ii) the model includes at least two active agents; and (iii) the model includes one or no active agents, but it exhibits a non-trivial and unpredictable system evolution over time.

Table 2. Minimum criteria for classifying an ABS model as Green Flag (see also [36]).

Condition	Description	Green Flag Eligibility
(i) Interaction	Presence of direct or indirect interactions among agents.	Mandatory
(ii) Two or more active agents	At least two agents show autonomy, adaptivity, or goal-orientated logic.	Sufficient if (i) is met
(iii) System evolution	System dynamics change over time due to agent behaviours.	Alternative to (ii), if (i) is met

Evidently, condition (ii) does not exclude condition (iii); in fact, when the model includes a reasonably large number of active agents, it is highly likely that the system will exhibit a distinct evolutionary pattern over a sufficiently long-time horizon. Relative to condition (iii), if criterion (i) is satisfied, given the near-exclusive presence of passive agents, interactions can only occur indirectly. Nevertheless, a high number of agents may give rise to a form of collective intelligence that emerges gradually because of system-level evolution.

This classification, therefore, suggests a dichotomy between the two different types of Green Flag models. At one end of the spectrum, we can find models satisfying conditions (i) and (ii). These are referred to as "Active Agent Models", a label that emphasises their ability to capture decentralised reasoning, goal-orientated behaviour, and micro-level decision making. At the other end we find models that fulfil conditions (i) and (iii) and that, therefore, we decided to label as "Emergent Colony Dynamics". These models leverage agent-based logic to simulate population-level effects that emerge from the interactions of minimally autonomous or even passive agents. Evidently, many models may fall somewhere in between these two extremes, whereas models that incorporate all three features are classified as "Full Spectrum Models".

5.2. Contextualisation of the Classification Scheme

For the sake of clarity, and to contextualise the proposed classification scheme, in this section we detail the review process of the studies that we analysed, and then we examine in detail three studies that perfectly match the previously defined categories: one study is classified as Red Flag, and two as Green Flag, positioned at opposite ends of the classification spectrum. Each article will be briefly summarised and evaluated according to the classification scheme introduced earlier. Lastly, we will present an excerpt of the classification table (Table 3) generated after analysing all 58 contributions.

Table 3. An extract of the "Article list, description, and classification" table, limited to the two Green Flag models described in Section 5.2.

Ref.	Ind. Sector	Context and Objectives	Justification for ABS	Simulation Objects	System Evolution	Interaction Type
[41]	Manufacturing	**Corporate social responsibility issues within buyer–supplier relationship**. The study examines how technical assistance (TA) programmes initiated by buyers influence the CSR performance of suppliers within a regulatory environment characterised by periodic inspections. It introduces a dynamic, multi-period model of buyer–supplier regulator interactions, accounting for risk preferences, bounded rationality, and uncertainty. The core objective is to evaluate how these behavioural and institutional mechanisms drive CSR improvements or deterioration over time, offering insights for both corporate strategy and regulatory policy design.	The authors use a multiagent simulation to model how buyers and suppliers adapt to inspections, penalties, and technical assistance. ABS is justified by the need to capture heterogeneous risk preferences, bounded rationality, and temporal learning within an SC. The framework supports sequential, contingent decision making (e.g., delivering TA, upgrading CSR practices, reacting to regulatory thresholds), across multiple periods, which would be analytically intractable.	**(1) Buyer agents**. Each buyer is linked to a single supplier and decides whether to offer technical assistance (TA) based on the supplier's perceived CSR level and its own risk preference. These decisions are dynamically updated in response to regulatory inspections or past TA outcomes. **(2) Supplier agents**. Based on their current CSR level, risk preference, and absorptive capacity, suppliers choose whether to upgrade or downgrade their CSR practices in response to buyer incentives and the perceived probability of inspection. **(3) Regulator agent**. An exogenous actor that conducts random inspections, penalises underperforming suppliers, and periodically adjusts CSR thresholds. It indirectly influences buyer and supplier behaviour through deterrence effects.	The system operates through repeated three-phase cycles: **(1) Decision phase**. Buyers and suppliers make CSR-related choices based on risk–cost trade-offs. **(2) Inspection phase**. The regulator performs inspections and applies penalties when CSR thresholds are not met. **(3) Update phase**. CSR levels and buyer perceptions are revised based on observed outcomes. Across multiple iterations, adaptive behaviours emerge; for example, opportunistic CSR downgrades by suppliers following inspections, or increased TA investments by risk-averse buyers under heightened regulatory pressure.	**Buyer–Supplier**. The agents interact through the provision of technical assistance (TA) and updates to supplier reputation, influenced by CSR performance and the supplier's absorptive capacity. **Supplier–Regulator**. Suppliers are subject to inspections, with penalties applied when CSR thresholds are not met. **Buyer–Regulator**. Buyers are indirectly affected by the performance of their suppliers, primarily via reputational risks. Although these interactions are indirect and state-dependent, they shape agent behaviour over time through feedback loops driven by the gap between perceived and actual CSR levels.
[42]	Agriculture	**Food Supply Chains: Animal Welfare in Pork Production** This study explores how public debates, particularly around animal welfare in Dutch pork production, influence the adoption of sociotechnical innovations in food supply chains. Combining dramaturgical analysis with agent-based simulation, it examines how stakeholder interactions and media-driven events shape societal norms and drive structural change. The aims are twofold: (1) to validate hypothesised behavioural dynamics from content and discourse analysis, and (2) to explore how shifts in public opinion and SC practices might have unfolded under alternative behavioural or external event scenarios.	The authors justify ABS as the appropriate tool to capture the heterogeneous, adaptive behaviours of consumers, producers, retailers, and NGOs engaged in public discourse on food ethics. ABS effectively models opinion dynamics and emergent change, reflecting how bottom-up interactions and external shocks (e.g., media events) can drive long-term transformations in production practices. It enables micro-level reasoning, evolving feedback, and patterns of opinion convergence or divergence critical to understanding policy-relevant transitions.	Four main agent classes, segmented into subtypes are adopted. **Consumers** (8 types). Defined by their orientation (e.g., price or welfare-sensitive) and responsiveness to media events. They form opinions through interactions with NGOs, peers, and retailers. **Producers** (5 types). Represent farmers with varying balances of economic and ethical concerns, influenced by peer interactions, the producers' organisation, and retail demand. **Retailers** (4 types). Ranging from passive to proactive, capable of adjusting supply chain standards in response to market signals and NGO pressure. **NGOs** (3 types). Include one activist NGO (with fixed welfare stance), one moderate NGO (with flexible position), and a producers' organisation (risk-averse but adaptable). All agents' behaviours are governed by bounded confidence opinion dynamics equations with asymmetric thresholds.	The simulation runs in weekly time steps over a ten-year period. Agents exchange opinions shaped by their social networks and sporadic media events, which may increase receptiveness to opposing views. As certain stakeholder clusters align (e.g., moderate NGO and a proactive retailer), critical tipping points can emerge, triggering system-wide shifts toward animal-friendly production practices. In their absence, the system may instead exhibit opinion polarisation or stagnation. By testing hundreds of parameter configurations, the simulation highlights the fragile conditions under which meaningful systemic change can unfold.	**Consumers–NGOs**. The agents exchange narratives and cues, with media events enhancing consumer responsiveness. **Consumers–Consumers**. Peer interactions drive gradual opinion shifts or reinforcement. **Consumers–Retailers**. Feedback loops influence retailer behaviour and responsiveness. **Retailers–Producers**. Retailers demand more ethical practices, prompting producer adaptation. **Producers–Producers' Organisation**. Norm adoption shaped through internal alignment and peer influence. **NGOs–Retailers/Producers**. The agents exert pressure, propose compromises, or lead advocacy efforts. All interactions follow structured yet probabilistic opinion convergence, with asymmetric susceptibility reflecting real-world biases and power imbalances.

5.2.1. Details of the Review Process

All 58 papers were thoroughly read and analysed in detail, in accordance with the classification method described in Section 3 and the Green Flag–Red Flag categorisation approach introduced in Section 5. Specifically, the review process involved a total of four researchers. The group was divided into two subgroups, each assigned to review half of the papers. Within each subgroup, the researchers independently analysed and classified the articles. In cases where discrepancies emerged, the "uncertain" papers were also reviewed by the two remaining researchers, followed by a collective discussion. If, even after discussion, a unanimous agreement could not be achieved (a fact that occurred only once) a majority decision was adopted. Although no formal inter-rater agreement metric was employed, we believe that this multi-stage procedure offers a sufficiently robust and reliable framework, consistent with the overall goals of the study.

5.2.2. Active Agents—Green Flag Model

Ref. [41] investigates how technical assistance initiatives by buying firms and regulatory inspections influence suppliers' corporate social responsibility (CSR) performance. The model involves three types of agents, namely, buyers, suppliers, and regulatory authorities, each one characterised by heterogeneous attributes such as risk preferences, internal states, and context-sensitive decision rules. Suppliers are further defined by their absorptive capacity, which determines their ability to internalise and act upon the technical assistance they receive. The model accurately reproduces the decision-making process by which buyers assess whether to help based on their perception of a supplier's CSR level and anticipated regulatory risks, while regulators perform periodic inspections and impose penalties according to a dynamic CSR threshold. In doing so, the model effectively captures the complex interplay between regulatory oversight, buyer strategies, and supplier compliance in a multi-period supply chain context. What distinguishes this model is its dynamic feedback architecture. Agents do not operate according to fixed rules; instead, their behaviour adapts in response to experience, regulatory pressure, and the perceived trustworthiness of their partners. These changes are driven by cost–risk trade-offs that agents evaluate at every time step, leading to emergent, system-wide patterns of either trust reinforcement or erosion. Although agent interactions are not implemented in a direct or explicit way, the model integrates several forms of indirect interactions (e.g., perceptual feedback, institutional influence, and reputation dynamics) that shape agents' adaptive responses and drive the long-term evolution of the system.

Considering these features, ref. [41] clearly satisfies condition (i), i.e., the presence of indirect interactions, as well as condition (ii), i.e., the inclusion of active agents. For these reasons, it is classified as a "Green Flag" model of the "active agent" type.

5.2.3. Emergent Colony Dynamics—Green Flag Model

Ref. [42] explores how public debate and public concern can trigger sociotechnical innovations in food supply chains, using the Dutch pork sector as a case study. Key actors, such as activist and moderate non-governmental organisations (NGOs), consumers, retailers, and producers are identified, and their roles in shaping public opinion and institutional responses are reproduced in an agent-based simulation that models opinion dynamics among heterogeneous stakeholders. All the agents are modelled as relatively simple entities with limited internal states (e.g., opinion, uncertainty, openness). However, their indirect interactions, mediated by the media and NGOs, give rise to complex, path-dependent transformations at the system level. For instance, it is shown that, under certain conditions, a turning point in public discourse can be reached, shifting the system toward the widespread adoption of animal welfare practices. While the agents themselves do not exhibit cognitive sophistication, the collective behaviour of the system evolves dynamically, showing clear hallmarks of emergent complexity.

Therefore, although ref. [42] does not satisfy condition (iii), as it does not incorporate active agents, it clearly fulfils both conditions (i) and (ii), since the ABS leverages indirect interactions and exhibits unpredictable evolution over time. Given this, the model qualifies as a Green Flag and, while it may not represent a perfect archetype, it is the closest representative (within our dataset) of what we define as Emergent Colony Dynamics.

5.2.4. Red Flag Model

Ref. [43] presents a novel approach for optimising supply chain ordering management, by combining an ABM with reinforcement learning (RL). It models a four-echelon SC, comprising a retailer, distributor, manufacturer, and supplier, where each agent makes weekly decisions based on its local state and demand, which is non-stationary. The merits of the paper are undeniable, as it introduces a novel and intelligent simulation-based optimisation framework and enables the definition of near-optimal ordering policies that contribute to stabilising inventory levels under fluctuating demand. Nonetheless, ref. [43] is classified as a Red Flag model because the nature of the agents included in the simulation fails to meet our inclusion criteria. Specifically, the agents lack meaningful autonomy, interactivity, and adaptive capacity in relation to the system they inhabit. Firstly, their behaviour is constrained to static rule-based policies, with no evidence of social or systemic adaptation. The integration of Q-learning into individual agent decision making is, in practice, a reinforcement of local optimisation rather than agent-level learning in a broader sense. In addition, the agents are optimised in isolation, with their policies shaped only by internal cost functions and inventory states, rather than by the evolving behaviour or the performance of other agents in the network. Secondly, there is a complete absence of interactions and influence between the agents. They only respond to system events without any other strategies or actions. For these reasons, the agents in this model function more as independent optimisation units than as autonomous, socially situated entities. The absence of system-aware adaptation, interactive decision making, and behavioural complexity suggests that the model could just as effectively have been implemented using a standard discrete event simulation or a similar approach.

Finally, it is worth noting that this article clearly demonstrates that a Red Flag classification does not imply a "poor model" but rather reflects the limited suitability of an ABM for the specific case under study.

5.2.5. A Subset of the Classification Results

For the sake of clarity, Tables 3 and 4 present a subset of the classification results, limited to the three use cases discussed in Section 5. The complete article list, description, and classification table are available via the DOI link provided in the "Data Availability Statement" following the conclusions. Please note that, for the sake of readability and due to space constraints, the table text has been shortened (compared to the extended version) without compromising its clarity or content quality.

Table 4. An extract of the "Article list, description, and classification", limited to the Red Flag models described in Section 5.2.

Ref.	Ind. Sector	Context and Objectives	Justification for ABS	Simulation Objects	System Evolution	Interaction Type
[43]	Wood	<u>Wood SC</u> The study examines how energy price fluctuations impact the bullwhip effect on the wood extraction supply chain. It introduces a simulation-based optimisation framework that integrates an ABM with reinforcement learning, to model and optimise order management policies across a four-echelon supply chain under non-stationary demand conditions.	The authors used AnyLogic for modelling, justifying their choice by highlighting its agent-based paradigm, where system components are represented as autonomous, self-organising agents capable of decision making and communication. These agents operate based on defined rules, making ABS well-suited to capturing the non-linear dynamics of complex systems.	Four agent types are used. **Retailer agent**. Manages customer demand while accounting for inventory levels, as well as order-related setup, maintenance, and transportation costs. **Distributor agent**. Processes weekly orders from the retailer, either fulfilling them immediately or recording them as backorders until the next inventory replenishment. **Manufacturer agent**. Receives weekly orders from the distributor and manages both raw material and finished goods inventories. It seeks to fulfil orders while avoiding backorder penalties, making it the most complex agent in the simulation. **Supplier agent**. Supplies raw materials and components. It processes weekly orders based on current inventory levels, fulfilling requests when possible or incurring penalties for unfulfilled orders.	The model simulates the flow of goods by tracking inventory levels and order dynamics, while optimising transport routes to balance supply and demand across the supply chain. System evolution is absent, as the objective is to obtain near-optimal replenishment policy under non-stationary-demand and using the Q-learning algorithm.	Interactions are purely procedural. Agents adjust inventories and order quantities in response to upstream and downstream signals, without explicit coordination mechanisms. There is no negotiation, messaging, or direct agent-to-agent influence beyond standard material and information flows typical of supply chains. Coordination emerges solely from isolated reinforcement learning processes, shaped by shared environmental constraints such as holding costs, delivery delays, and backorder penalties. Agent behaviour is thus reactive and system-driven, rather than socially or strategically interactive.

6. Results and Discussion

In this section we stress the separation between Green and Red models and we report some descriptive statistics of our results, also considering agents' interactions and motivations for using ABS.

6.1. Green vs. Red: Model Divison

The application of the categorisation approach led to the identification of 37 Red Flag and 21 Green Flag articles. As shown in Table 5, the Green Flag ones were further grouped into the three categories (namely, Active Agent Model, Emergent Colony Dynamics and Full Spectrum), as detailed in Section 5.

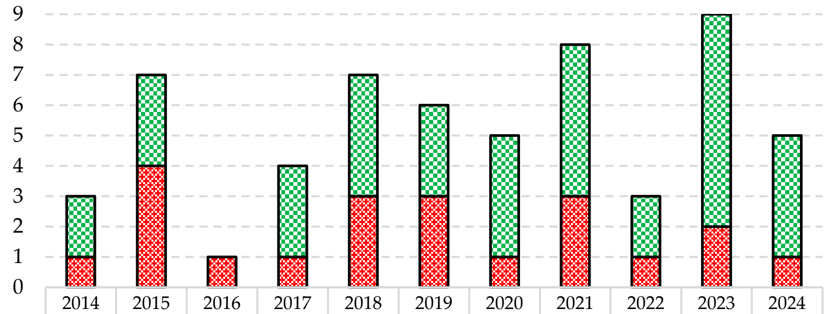
Table 5. Model subdivision into classes.

Flag	Number	References
Red	37	[43–79]
Green—Active Agent Models	7	[41,80–85]
Green—Emergent Colony Dynamics	6	[42,86–90]
Green—Full Spectrum	8	[91–98]

The following subsections provide a more detailed analysis of this initial categorisation and highlight the most insightful outcomes of the analysis.

6.2. Timeline, Simulation Techniques, and Sectors

Figures 5–7 show the distribution of the Red and Green Flag articles over time, across sectors, and by the type of simulation employed. What is particularly interesting is the almost constant coexistence of Red and Green Flag models, with a proportion that has remained relatively stable over the years. This suggests that the use of non-essential ABS models has been a recurring feature, at least in simulations related to the SC. Only in recent years (i.e., 2020 to 2024) does the proportion of Green Flag models appear to be increasing, and this could indicate a better understanding of ABM implications and reflect a growing need to consider end-customer behaviour as an essential element in designing resilient SCs. However, this is merely a tentative interpretation of the figure. If such a trend exists, it is limited to the most recent years, and the available data are not enough to support any robust statistical inference.



	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024
Green Flag	2	3	0	3	4	3	4	5	2	7	4
Red Flag	1	4	1	1	3	3	1	3	1	2	1

Figure 5. Temporal trends of Green and Red Flag models.

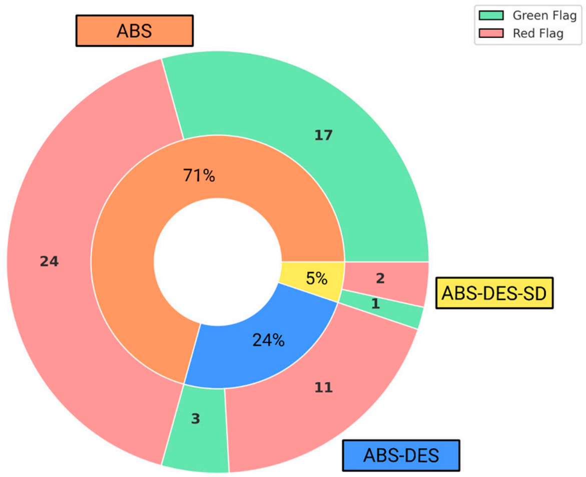


Figure 6. Distribution of different modelling techniques.

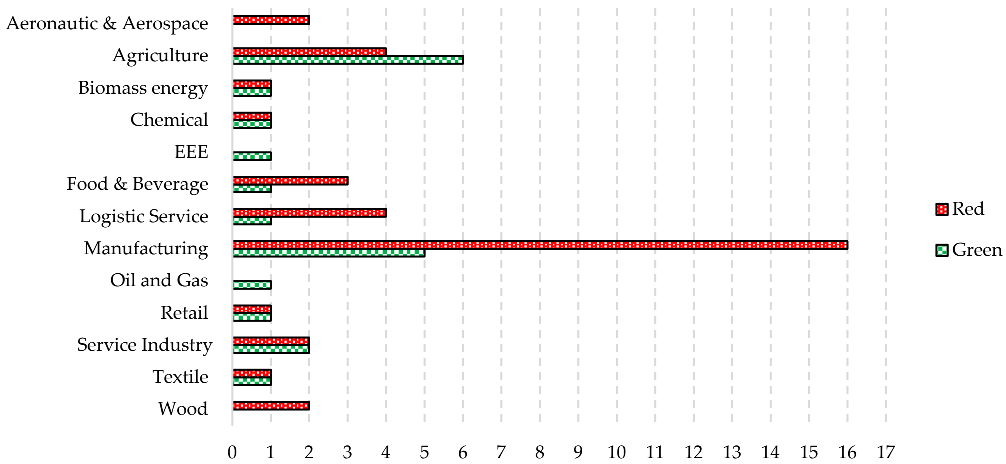


Figure 7. Green and Red Flag models through industrial sectors.

To better understand how methodological choices relate to this classification, Figure 6 provides a breakdown of the models by simulation technique. Specifically, it displays a sunburst chart illustrating the distribution of Red and Green Flag models across three simulation types: ABS, Hybrid ABS-DES, and Hybrid ABS-DES-SD. The inner ring represents the simulation categories, while the outer ring shows the proportion of Red and Green Flag models within each category.

As the inner ring indicates, most of the works, that is, 71% of the total, are purely based upon ABS. Also, as the outer ring indicates, within this group Red Flag models prevail, being around 58.5% of the total (i.e., 24 out of 41). This imbalance in favour of Red Flag models becomes even more pronounced, around 76.5%, in the case of hybrid models integrating ABS and other simulation approaches. This fact further highlights that ABS is rarely leveraged to its full potential and that often it has been employed, let us say, by convention, with agents that have been used even in simulation scenarios that could also be implementing DES or SD approaches. This tendency might be explained by the widespread availability of multi-paradigm simulation software, such as AnyLogic, which allows for the implementation of different modelling approaches within a unified framework, often encouraging the adoption of agent-based solutions even when they are not strictly required. Unfortunately, it was not possible to accurately quantify the software used for each model or to make meaningful comparisons across programming languages, as only a small fraction of the articles included even partial access to the source code.

Excluding the sectors characterised by very low sample sizes, the predominance of Red Flag models over Green Flag ones is evident even when stratifying the data by sector, as is clearly shown in Figure 7. The imbalance is particularly evident in the manufacturing sector, which also accounts for the largest number of studies (i.e., a total of 21 contributions, 16 of which are labelled as Red Flag and the other 5 as Green Flag). A notable exception to this trend can be traced in the agricultural sector, where Green Flag models appear proportionally more frequent (6 out of a total of 10 contributions), reflecting the inherent suitability of this domain for decentralised and adaptive modelling approaches. Although the sample size does not allow us to make statistical inferences, this may be due to the complex, distributed nature of agricultural systems, where agent interactions and local decision making play a fundamental role in shaping system behaviour.

6.3. Inter-Agent Interactions

This subsection focuses on the nature of inter-agent interactions that provides a strong proxy for assessing the depth and granularity of the modelling approach. As expected, and as clearly demonstrated by Figure 8, most Red Flag models exhibit either no interactions or rely exclusively on indirect effects, such as shared environmental cues. Only a limited number of Red Flag studies make use of direct and/or indirect interactions, yet they were not labelled as Green Flag articles due to their failure to meet requirements (i) and (ii), as defined in Section 5.

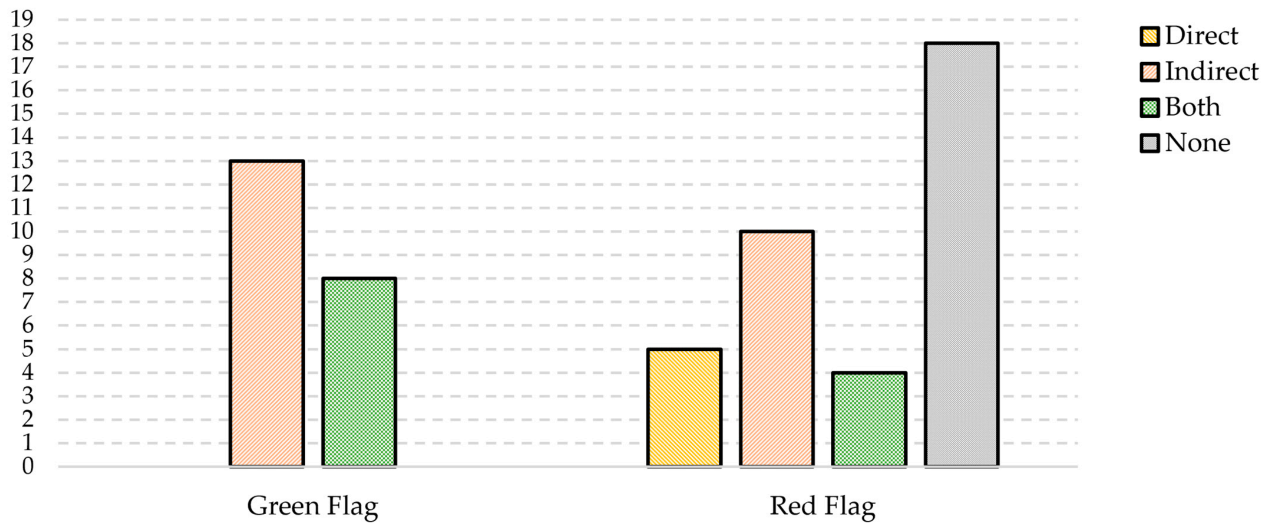
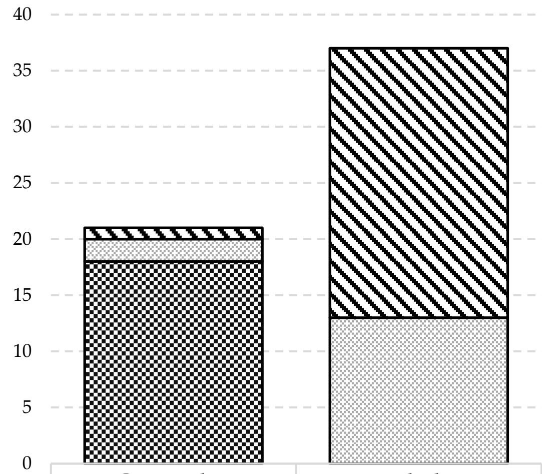


Figure 8. Interactions within models.

Conversely, the Green Flag models display a broader and more nuanced spectrum: many incorporate both direct and indirect interactions, reinforcing the idea that intentional agent influence, whether peer-to-peer or system-mediated, is a key component of robust ABS implementations in SC contexts.

6.4. Declared Motivations for Using ABS

In this paragraph, we provide a last analysis made considering the second classification parameter of Table 1, that is, the "*Motivation for ABS*" given by the authors. Specifically, Figure 9 shows the level of coherence between the stated motivation and the implemented model, for both the Green and Red Flag cases. Note that, in this context, we define the degree of coherence as the alignment between the authors' stated motivations for employing ABS and the actual features of the implemented models. For instance, in the case of a Green Flag, high coherence indicates that both the model's structure and its operating logic perfectly match the declared need for agent-based dynamics. Conversely, a low coherence indicates that the authors' descriptions understated the actual complexity or features of the implemented model. For Red Flag papers, coherence is defined in a specular manner, so that low coherence reflects situations where the authors overstated the model's features relative to what was actually implemented. In this regard, we would like to point out that the assessment of the coherence levels was conducted following a procedure like the one described at the beginning of Section 6. Specifically, the evaluation was carried out by the same panel of four experts, using a consensus-based approach. Each expert independently reviewed the materials, and any disagreements were resolved through discussion, ensuring consistency and methodological alignment across the entire analysis.



	Green Flag	Red Flag
Low	1	24
Fair	2	13
High	18	0

Figure 9. Degree of coherence between authors' justifications and simulation model.

As expected, the level of coherence is very high for Green Flag models; the authors had a clear understanding of the need to implement an ABM and they supported their choices with conceptually strong justifications, such as the need to capture decentralised decision making or emergent dynamics. The situation is the opposite for Red Flag papers, where a consistent mismatch can be observed between the stated motivations and the features implemented in the models. Many studies present highly articulated motivations that, however, are not reflected in the simulation model they propose. This indicates that the declared intention does not always translate into a model that effectively leverages the core features of ABS and further suggests that the conceptual distinction between DES and ABS is not always clearly articulated in research practice.

To conclude this section, we want to make it clear that our analysis does not aim to judge the quality or usefulness of these models, but rather to reflect on whether the agent-based paradigm is being conceptually and operationally exploited. The findings highlight a disconnect that is often more methodological than intentional, underscoring the need for clearer alignment between modelling goals, declared motivations, and simulation architecture.

7. Conclusions and Future Developments

In this work, we analysed a total of 58 studies employing an ABM within the domain of SC modelling. Our primary objective, as stated by the third research question, was to determine whether ABS is being used to its full potential, a concern that was already highlighted in the literature, but to which no quantitative response has been offered so far. To this end, and in response to research questions (i) and (ii), we developed an original taxonomy that enables practitioners to classify ABMs based on three core technical dimensions: the internal functioning of agents, the nature of their interactions, and the capacity for system-level evolution over time. Models that genuinely required an agent-based approach to capture the described SC dynamics were labelled as Green Flags, while those whose behaviour could be replicated using more traditional paradigms were labelled as Red Flags.

7.1. Main Findings

Somewhat unexpectedly, only 36% of the models qualified as Green Flags. In particular, the absence of meaningful interaction among agents emerged as the most frequent reason for exclusion. Notably, the Red Flag models, despite often being complex and well-structured, could have been entirely replicated using DES or other simulation approach, without any meaningful loss in behavioural fidelity. Even among the Green Flag models, only a third met all the criteria for Full Spectrum ABS. The remainder either lacked a clear evolutionary dynamic or featured reactive agents with fixed decision rules. This pattern may reflect a broader methodological inertia, as authors familiar with ABS may continue to apply the paradigm even in contexts where it is not strictly necessary. This impression is reinforced by the number of Red Flag models that were accompanied by conceptually sound justifications yet misaligned with the implemented simulation architecture. The growing availability of hybrid simulation platforms, which allow for the definition of "agents" that behave more like event-driven components, may also blur methodological boundaries, and contribute to conceptual ambiguity.

7.2. Possible Implications for Contributors and Developers

Although designed to assess the percentage of SC-related works that appropriately use the ABS technique, the Green–Red Flag classification framework seeks to provide conceptual clarity by distinguishing between authentically agent-based models and those that merely adopt the label without substantively engaging with the paradigm. It offers a structured lens through which scholars and model developers can critically evaluate the use of ABS, paving the way for more rigorous, transparent, and meaningful simulation practices. In particular, the framework can be used prospectively, guiding developers during the early stages of model design. By prompting key questions, such as whether agents with utility functions are needed, whether non-trivial agent interactions are expected, or whether the model seeks to explore emergent scenario evolution, it helps determine whether ABS is truly warranted for the problem at hand. Furthermore, insights into the proper implementation of ABS can be drawn by examining the characteristics of Green Flag models, as detailed in the complete classification table provided in the online Supplementary Material. This table also offers a broad overview of the existing body of ABS applications in the supply chain domain, thereby providing a useful point of reference for situating one's own work within the current research landscape.

7.3. Limitations of the Research

Despite the rigour of our classification framework, several challenges emerged during its application. The considerable heterogeneity of the models often made consistent classification difficult, with several borderline cases involving ambiguous dynamics or loosely defined agent interactions. In many instances, crucial information about agent behaviour and system evolution was only partially described or entirely absent, requiring us to infer structural features from indirect textual cues. The lack of source code or pseudocode further limited our ability to validate assumptions or reconstruct simulation logic. Moreover, the nature of SCs may not always lend itself naturally to "pure" ABS. For this reason, some models were deemed acceptable as Green Flags despite their limited reconfigurability, provided they incorporated rich behavioural logic and plausible inter-agent influence.

7.4. Future Works

Although originally conceived for the SC domain, our classification scheme could be extended to other contexts. Indeed, the agent classification parameters have been intentionally defined in a generic manner, as they directly refer to fundamental characteristics of agents, regardless of the specific domain in which they are applied. Therefore, future research could be made to extend the classification framework to other emergent domains, such as urban mobility, where ABS is frequently adopted. This would allow for the exploration of whether the insights obtained in the present study also hold in different settings and would allow for a broader validation of our criteria and may reveal domain-specific modelling patterns or pitfalls.

Another possible direction for future works could be to either extend the framework with a more granular typology or introduce formal metrics and validation criteria to make the classification process less subjective and more robust. However, such modifications are not straightforward and may entail certain risks. Indeed, given the wide heterogeneity of the models proposed in the literature, it is not always possible to identify common technical elements. Moreover, as the level of granularity increases, so does the amount of information required for classification, information that is often not available in the article itself unless the authors have made their simulation code publicly accessible. As a result, excessive granularity could significantly reduce the number of classifiable articles, potentially undermining the usefulness of the entire approach. This is certainly an aspect that requires careful consideration.

Supplementary Materials: The following supporting information can be downloaded at: https://data.mendeley.com/datasets/yfx4f9f6fb/1, accessed on 26 June 2025.

Author Contributions: Conceptualisation and design, G.R. and F.Z.; methodology, F.M. and F.Z.; formal analysis, investigation, and validation F.M., M.G., G.R. and F.Z.; data curation, F.M.; writing—original draft preparation, F.M.; writing—review and editing, M.G., G.R. and F.Z.; visualisation, F.M.; supervision, M.G. and F.Z.; funding acquisition G.R. All authors have read and agreed to the published version of the manuscript.

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