A Text Mining-Based Thematic Review of Multi-Agent Systems in Supply Chain Optimization and Decision Support

Abstract:

This study conducts a comprehensive thematic analysis of 437 Scopus-indexed documents to explore the evolving landscape of multi-agent systems (MAS) in supply chain management. Five dominant research clusters are identified using a text mining methodology, capturing key developments in real-time decision support, distributed optimization, agent-based coordination, intelligent logistics, and sustainable operations. The findings highlight how MASs are increasingly integrated with mixed-integer programming, reinforcement learning, and cyber-physical systems to address last-mile delivery, inventory control, and disruption management. Unlike prior reviews focused on isolated MAS applications, this study presents a cross-cutting synthesis of technological and managerial trends that shape digital supply chain ecosystems. Challenges such as scalability, agent interoperability, and real-time coordination under uncertainty are critically examined. Strategic insights and future research directions are proposed to guide the design of interpretable, hybrid MAS frameworks that support agile, sustainable, and resilient production and logistics systems. This review advances production research by offering an evidence-based roadmap for leveraging MAS in complex supply chain environments. It supports decision-makers in aligning technological innovation with operational performance and strategic goals.

Keywords:

Multi-agent systems; Supply chain optimization; Intelligent agents; Decision support systems; Last-mile logistics; Distributed artificial intelligence.

# Introduction

Multi-agent systems (MASs) in supply chains represent a foundational shift from centralized control architectures to decentralized, autonomous networks capable of managing complexity, uncertainty, and dynamic interactions across production and logistics environments. Defined as distributed computational systems, MASs are intelligent, autonomous software agents that interact, negotiate, and collaborate to simulate coordinated decision-making processes across diverse supply chain functions (C. Chen & Xu, 2018; C. Yang et al., 2018; C. Yu & Wong, 2015). Each agent operates with localized intelligence yet contributes to collective goals, enabling the system to self-organize and adapt to disruptions, demand fluctuations, or conflicting constraints (Baena et al., 2020; Rzevski et al., 2018; B. Sun & Sun, 2016). This autonomy fosters flexibility and resilience in networks challenged by evolving market demands, interdependencies, and environmental pressures (Kessentini et al., 2019; Ponnambalam et al., 2015; Skobelev, 2018). The literature consistently identifies MASs as decision-aid models that improve coordination, enhance planning accuracy, and support adaptive scheduling and resource allocation (Z. Li et al., 2019; Padmavathi et al., 2016; Rebollo et al., 2018). These models are particularly well-suited for distributed environments, where they align stakeholder objectives without centralized oversight, enabling collaborative responses to logistical challenges (Achatbi et al., 2020; Laouadi et al., 2017; Yan, 2015). MASs extend their relevance by modeling complex adaptive systems, offering real-time negotiation capabilities, and facilitating multi-objective optimization—characteristics that are central to modern supply chain intelligence (Bala et al., 2024; Darbari & Ahmad, 2019; Du et al., 2017; S. Liu et al., 2021; H. Zhang, 2024). In urban logistics and last-mile delivery, MASs are applied to manage decentralized transport systems by leveraging autonomous agents for real-time coordination among delivery vehicles, logistics firms, and even crowdsourced participants. These agents optimize delivery routes, balance economic and environmental objectives, and reduce traffic congestion and emissions by dynamically adapting to infrastructure and demand changes (Arishi & Krishnan, 2023; Bu, 2024; Dharmapriya et al., 2022; Gómez-Marín et al., 2023). This integration into city logistics underlines MASs’ scalability and sustainability, offering flexible frameworks that can be tailored to diverse delivery scenarios. Collectively, these approaches affirm MAS as transformative technologies that effectively support the strategic, adaptive, and operational objectives of modern supply chain systems. Their contributions to distributed intelligence, systemic resilience, and computational decision-making firmly position MAS at the forefront of innovation in production and logistics. Moreover, MASs directly align with key research areas in production research, including production system and supply network engineering, the analysis of essential behaviors of production resources and systems, the development of production strategies and related economic considerations, the formulation and evaluation of production policies, production planning, and scheduling, and the application of production research to service-oriented environments.

At the time of writing, only five documents published since 2015 are classified as reviews on MASs in supply chains in Scopus. Teo et al. (2015) evaluated the effectiveness and viability of urban distribution centers (UDCs) in city logistics using a multi-agent modeling approach supported by geographic information systems. The study addressed current challenges to delivery efficiency, such as depot distance, road restrictions, customer demands, and socio-environmental costs, which are exacerbated by increasing urbanization. Using a case study in Osaka City, Japan, the authors found that UDCs have the potential to reduce emissions; however, their sustainability depends heavily on the pricing of UDC services and the sensitivity of carriers to these charges.

Hanga and Kovalchuk (2019) provide a comprehensive survey on the application of machine learning (ML) and MASs in the oil and gas industry (OGI), highlighting the sector's complexity and the significant data management challenges it faces. The study outlines how AI—particularly ML—has been increasingly adopted to enhance efficiency, support maintenance scheduling, and prevent fraud. MASs, as a branch of distributed AI, are also noted for their suitability in managing the distributed nature of OGI operations. While both technologies show promise, ML has been applied mainly to isolated tasks, and MASs have seen limited real-world adoption despite favorable results in simulations. The authors argue that further research, especially on integrating ML within MASs, is crucial to unlocking their full potential and accelerating their acceptance in the OGI.

Dominguez and Cannella (2020) review the literature on multi-agent system applications in supply chain management, providing an overview of the state of the art. They highlight key industrial applications, examine generic frameworks used for supply chain modeling, and analyze the main topics addressed and the maturity of existing contributions in the field.

Herrera et al. (2020) review the integration of multi-agent systems and complex network theory in addressing systems engineering and management challenges across various engineering disciplines. It highlights how these approaches help manage complexity and dynamics in optimizing physical, natural, and virtual systems. The review also explores current and future research directions, focusing on theoretical advancements and industrial applications, including mesoscale, multiscale, and multilayer networks. Key application areas include smart infrastructure, manufacturing processes, and supply chain networks.

Ma et al. (Ma et al., 2025) present a systematic review of supply chain resilience from a network modeling perspective, emphasizing its growing importance amid increasing global complexity. It outlines the evolution and definition of supply chain resilience, using literature visualization to explore current research trends, challenges, and risk management practices. The study highlights the role of network modeling techniques, particularly complex networks and agent-based modeling, in simulating macro-level supply chain evolution and micro-level entity behavior. It assesses the strengths and limitations of these approaches and proposes future research directions, such as improving firm-level behavior modeling, analyzing information network dynamics, and designing task-oriented models. The findings suggest that enhancing supply chain resilience can yield widespread economic benefits, contributing to global stability and growth.

The necessity of a new review on MASs in supply chains is driven by both the rapid evolution of the field and the increasingly complex challenges faced by modern logistics and production systems. While previous reviews have contributed important insights, they often present a fragmented or narrow perspective, focusing on isolated applications, specific industrial sectors, or theoretical discussions without fully capturing the integrated impact of MASs across the broader supply chain landscape. The diversity of methodologies used and the absence of a consistent analytical framework have further limited the ability to derive generalizable conclusions or best practices applicable to complex, distributed logistics environments. Therefore, A new review is warranted to consolidate and critically examine the current state of research on MASs in supply chains, focusing on identifying dominant thematic areas, methodological trends, and gaps that hinder broader adoption and innovation. This review will provide a systematic and nuanced field mapping by employing text mining techniques—extracting and analyzing noun phrases from abstracts, titles, author keywords, and index keywords.

This review aims to systematically investigate and synthesize the current research on applying MASs in city logistics, urban freight, and last-mile delivery. The review seeks to uncover and critically examine the dominant thematic clusters within the literature using tech-mining techniques to analyze noun phrases (extracted from abstracts and titles), author, and index keywords. This data-driven approach identifies coherent research domains and supports a nuanced exploration of prevailing trends, critical challenges, and emerging opportunities. Through this comprehensive synthesis, the review intends to bridge existing knowledge gaps, enhance understanding of MAS applications in urban logistics, and promote the development of innovative, context-sensitive solutions. The resulting analysis will offer a structured roadmap for future academic inquiry and practical implementation, particularly as urban environments become increasingly complex and demand more flexible, intelligent, and resilient logistics systems. This review is also strategically aligned with the broader objectives of advancing production research. It contributes to developing decision-aid frameworks, optimizing planning and scheduling processes, and integrating intelligent technologies into modern supply chain and logistics systems. By addressing both the theoretical underpinnings and practical dimensions of MAS deployment, the review responds to the growing demand for scalable, adaptable, and computationally robust approaches to managing interdependent and dynamic logistics networks. As such, it offers a timely and relevant contribution to the ongoing transformation of urban supply chain systems.

The remainder of this paper is structured as follows: Section 2 outlines the materials and methods employed to conduct the review. Section 3 presents the main results derived from the analysis. Section 4 offers an in-depth examination of the dominant thematic clusters identified over the past decade. Finally, Section 5 summarizes the key conclusions and implications of the study.

# Materials and Methods

This section presents and discusses the methodology used. This research uses the standard workflow for literature analysis (Aria & Cuccurullo, 2017; Donthu et al., 2021; Page et al., 2021). The methodology used consists of the following steps:

1. Study design.
2. Data collection and preparation.
3. Data analysis.
4. Data visualization and interpretation.

## Study Design

**Table 1** details the study's parameters. The database chosen for information gathering was Scopus. Recognized for its broad and sophisticated capabilities, Scopus offers access to many global scholarly literature, comprehensive data, and analytical resources. It maintains a robust database containing over 93 million records, including over 28,000 active serial titles and over 327,000 books. Equipped with advanced search functionalities and filters, Scopus aids in the identification of pertinent sources, tracking of research trends or emerging topics, and the discovery of potential research collaborators (www.elsevier.com/products/scopus). This study distinguishes itself from earlier research by focusing exclusively on literature from the past ten years to pinpoint the most significant dominant trends.

**Table 1**

Parameters of the study.

Parameter Value

Database Scopus.

Years of Analysis From January 2015 to December 2024.

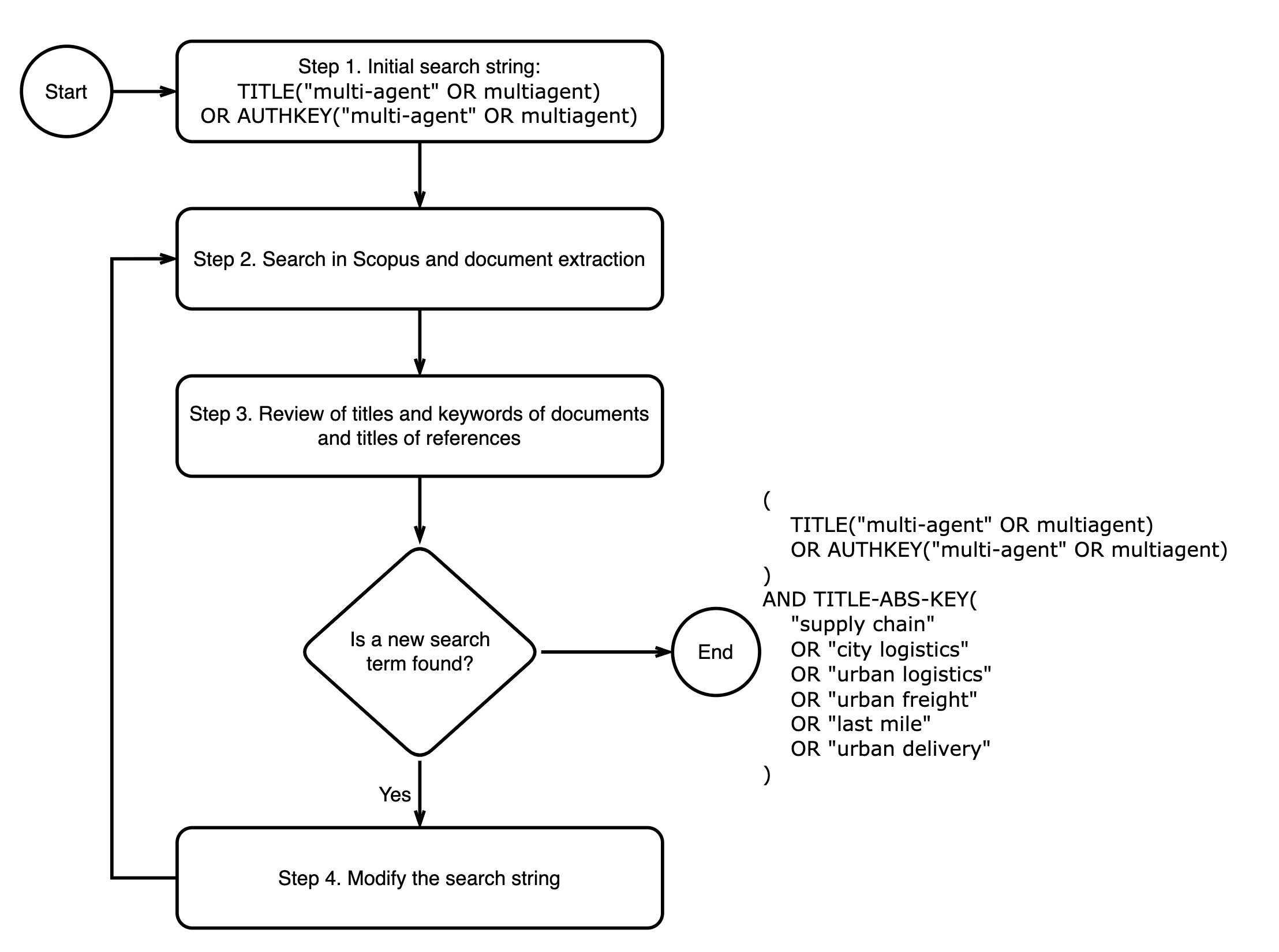
Data Retrieval January 30, 2025.

Search String It is derived using an iterative construction method, which will be elaborated upon in the subsequent section.

Inclusion Criteria Documents published in peer-reviewed journals and conference proceedings, books, and book chapters.

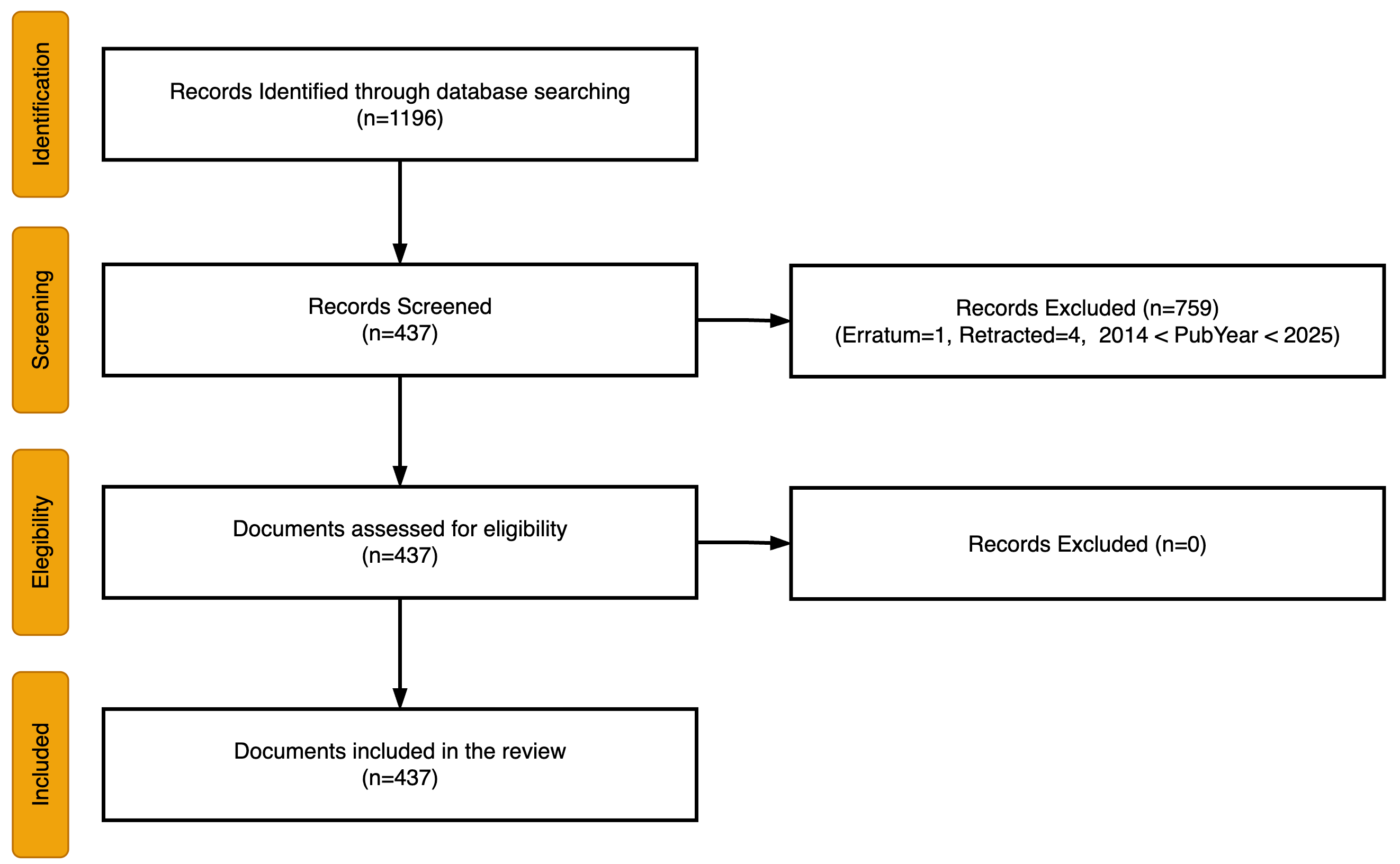
Exclusion Criteria Documents not related directly to the multi-agent methodologies applied to supply chains.

The objective of the search string is to capture all documents pertinent to MASs in supply chains using the iterative approach depicted in **Fig. 1**. The process begins with formulating the search string TITLE(“multi-agent” OR multiagent) OR AUTHKEY(“multi-agent” OR multiagent). This string is then utilized in Scopus to extract relevant documents that are unrestricted by time. An exhaustive review of these documents' titles and bibliographic references is performed to unearth any terms missing from the initial search string. Titles cited in the references are similarly examined. Newly discovered terms are then added to the search string, which is repeated until no further terms are found. It has also been confirmed that all pertinent search terms identified in the reviews are included. As a result, terms such as “city logistics” or “last mile” are added to the search string, as indicated in **Fig. 1**.



**Fig 1.** Search string design.

The finalized search string successfully extracted 1196 documents from the Scopus bibliographic database, as indicated in **Fig. 2**. During the subsequent document screening and selection phase, 759 papers were excluded. Reasons for exclusion included publication dates outside the range of 2015 to 2024, retracted documents, or erratum documents. As a result, the complete database for this study ultimately consists of 437 papers.



**Fig. 2.** The PRISMA flow chart.

## Data collection and preliminary preparation

The bibliographic data was sourced from Scopus in CSV format, with all available fields selected for download. The preparation of this data involved several steps to standardize the text strings, such as converting all text to uppercase, translating British English spellings into American English, removing diacritical marks, and harmonizing terminology. During the initial data preparation phase, noun phrases were extracted from the titles and abstracts of the articles. Subsequently, a new column named "descriptors" was created. This column integrates the author keywords, index keywords, and the extracted noun phrases, and it is intended to facilitate the discovery of dominant themes.

## Data Analysis

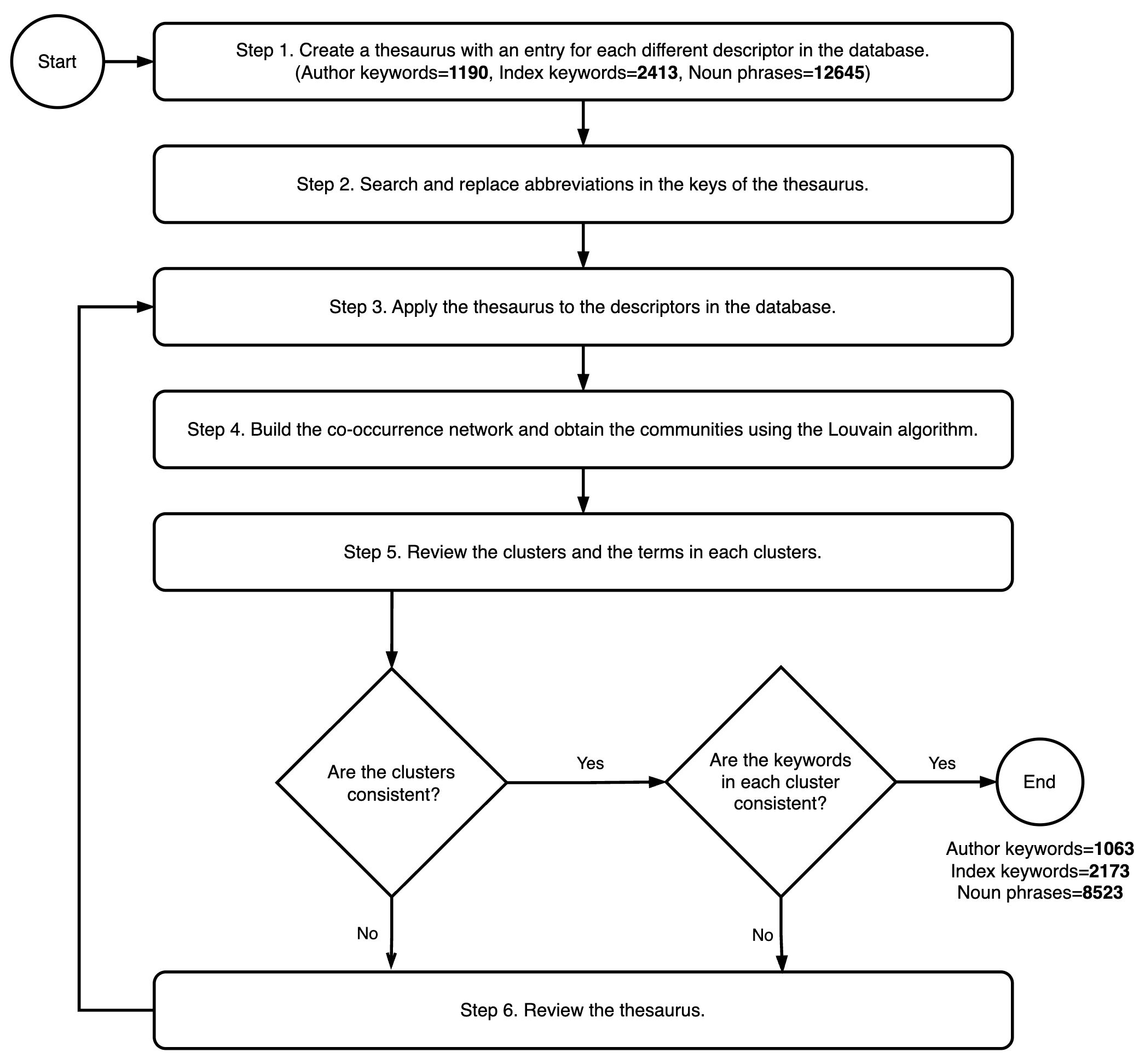
This study presents a systematic methodology to identify and analyze the dominant research themes about multi-agent systems in supply chains by combining advanced text-mining techniques with iterative manual refinement. The core of the method is based on creating and using a curated thesaurus built from a comprehensive set of document descriptors—specifically, author keywords, index keywords, and noun phrases extracted from the titles and abstracts of the analyzed documents. This approach, illustrated in **Fig. 3**, enables both the discovery of coherent thematic clusters and the refinement of the descriptor set through a data-driven yet interpretive process.

As emphasized in prior studies, clustering thematic content based on textual descriptors is fraught with linguistic challenges, such as variations in spelling, pluralization, abbreviations, and the presence of conceptually synonymous terms (Courseault Trumbach & Payne, 2007; Porter et al., 2019; Porter & Zhang, 2012; Y. Zhang et al., 2014). While normalization of orthographic variants can be automated, resolving semantic equivalences often requires manual intervention—particularly when scaling up to large databases. Thus, the algorithm presented in **Fig. 3** integrates automated text-mining procedures with human-guided validation to balance efficiency with conceptual accuracy. The complete methodological details are described in the work of Velásquez (2025). This study utilizes a new, currently under-development version of TechMiner, a Python package designed for bibliometric and tech-mining analysis (J. Velásquez, 2021).

The process begins by creating a thesaurus comprising 1,190 author keywords, 2,413 index keywords, and 12,645 noun phrases. Thus, this initial thesaurus contains 14,719 different terms after removing duplicated text strings. Next, all abbreviations within the descriptors are identified and systematically replaced with their complete forms (e.g., replacing "MAS" with "multi-agent systems"). This results in a preliminary harmonized set of document descriptors. Clustering is then performed using the Louvain algorithm on the co-occurrence network constructed from these descriptors. Document descriptors are filtered according to two rules. The first rule aims to discard low-frequency descriptors by establishing a minimum number of appearances. Descriptors with a lower number of appearances are discarded. The second rule uses a curated stopwords list containing overly general descriptors. Descriptors appearing in the stopwords list are discarded for analysis.

What distinguishes this approach, presented in **Fig. 3,** is its iterative nature. Each clustering iteration facilitates a manual review of the descriptors grouped within clusters, allowing the refinement of the thesaurus by merging conceptual synonyms and eliminating noise. This dual-purpose step—simultaneously discovering themes and validating descriptors—ensures that each cluster reflects a distinct and interpretable research topic within the multi-agents in supply chain literature.

Ultimately, the methodology condenses the descriptor set to 1,063 author keywords, 2,173 index keywords, and 8,523 noun phrases. The resulting clusters represent the dominant themes in the field and serve as the basis for subsequent critical analysis. This integrated, iterative process is especially well-suited to literature reviews and science mapping studies that aim to reveal structured insights in emerging, interdisciplinary domains such as multi-agent systems in supply chains.



**Fig 3**. Used methodology to obtain the dominant themes from paper descriptors.

# Results

## General Dataset Description

The dataset spans 2015 to 2024, containing 437 scientific publications with an annual growth rate of 29.88%. Most of these are either articles (215) or conference papers (182). The average document age is approximately five years, and each publication garners an average of 12.41 citations, translating to about 1.24 citations per year. A total of 1086 authors contributed to these works, with a level of international co-authorship at 21.72%. The involvement of 553 organizations from 59 countries underscores the global collaboration in the field. The dataset contains 14719 raw descriptors, obtained by combining author and index keywords and the noun phrases extracted from abstracts and titles. The cleaning process reduces the descriptors to 9651 different text strings.

## Discovered Dominant Themes

**Table 3** displays the five themes identified using the method outlined in **Fig. 3**. Only descriptors that appeared seven times or more were included in these calculations. This selection criterion covered 91.8 % of the documents in the database. **Table 3** displays the ten most frequently occurring descriptors per each discovered cluster. As commonly acknowledged, individual documents often address multiple themes simultaneously, which holds in this analysis and prevents assigning each paper to a single thematic category. **Fig. 4** illustrates the co-occurrence network of descriptors, where node size corresponds to the frequency of each descriptor within the dataset. The color and thickness of the connecting edges represent the strength of co-occurrence between descriptors. As expected, decision-making-related terms emerge as the most prominent descriptors, showing strong interconnections within the network.

**Table 3**

Dominant thematic clusters

Cluster Name Num Terms Percentage Main Descriptors

Intelligent Decision Ecosystems for Sustainable Supply Chains

41 42.7 Decision making; Decision support system; Sustainability; Sustainable development; Cyber-physical system; Supplier selection; Bullwhip effect; Information management; Information systems; Real-time.

Adaptive Learning Agents for Optimization

20 20.8 Reinforcement learning; Multi-agent reinforcement learning; Learning systems; Inventory control; Vehicle routing problem; Inventory management; Deep learning; Deep reinforcement learning; Learning algorithms; Heuristic-based methods.

Cognitive Infrastructures for Decentralized Supply Chains

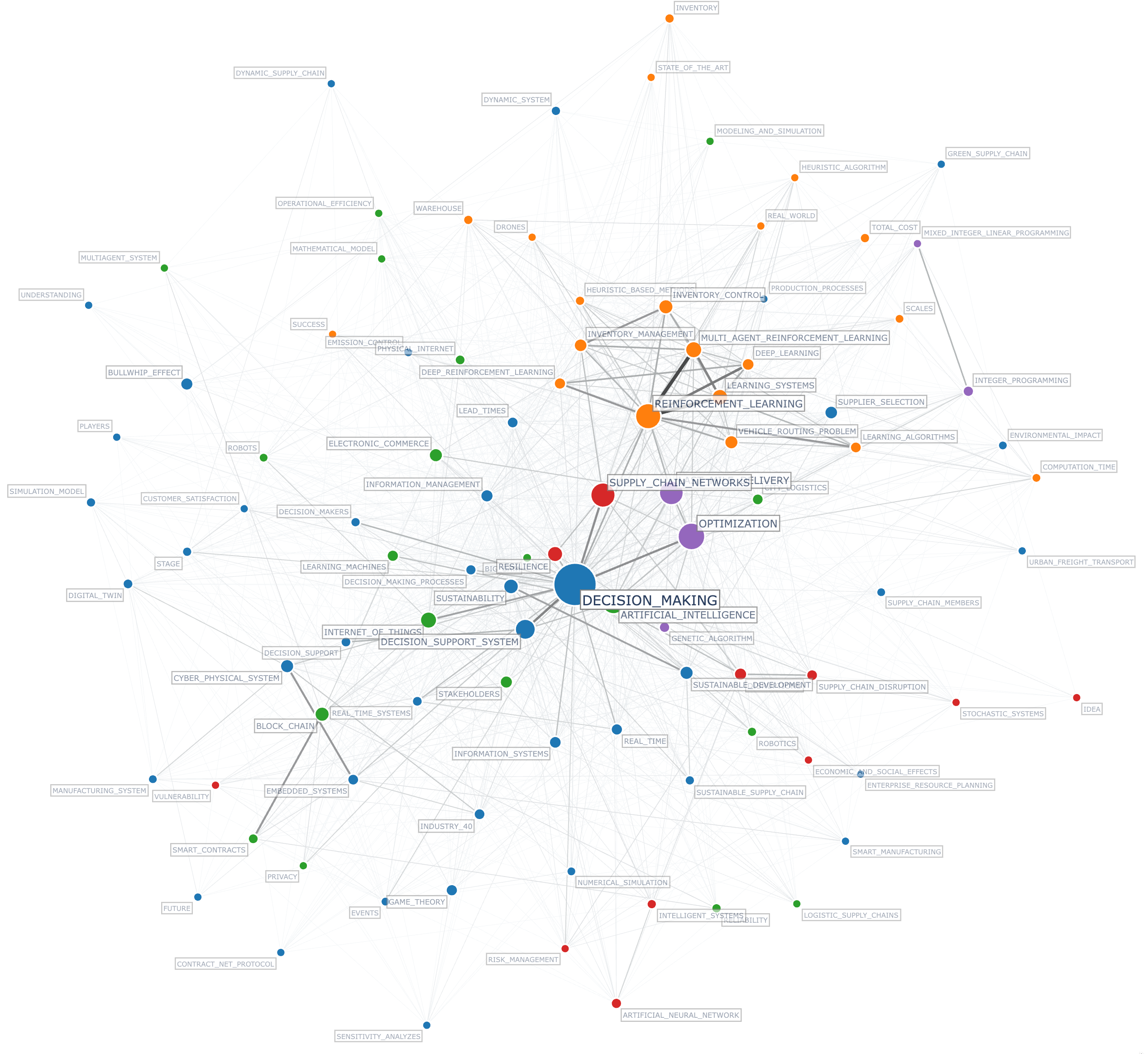
19 19.8 Artificial intelligence; Internet of things; Blockchain; Electronic commerce; Stakeholders; Learning machines; City logistics; Smart contracts; Physical internet; Robotics.

Resilient Intelligence in Distributed Supply Chains

11 11.5 Supply chain networks; Resilience; Disruptions; Supply chain disruption; Artificial neural network; Intelligent systems; Vulnerability; Risk management; Stochastic systems; Economic and social effects.

Intelligent Optimization for Last-Mile Logistics

5 5.2 Optimization; Last mile delivery; Integer programming; Genetic algorithm; Mixed integer linear programming.



**Fig 4.** Obtained clusters. Node colors indicate the cluster. Edge widths indicate the number of co-occurrences between descriptors.

# Discussion

This section critically reviews the dominant clusters in the most relevant literature published in the last ten years.

## Cluster 1: Intelligent Decision Ecosystems for Sustainable Supply Chains

Thematic developments across the reviewed literature illustrate a paradigm shift in supply chain systems from centralized, linear models to decentralized, intelligent ecosystems where MASs serve as the architectural core. MASs are increasingly integrated into cyber-physical and hyperconnected infrastructures—such as Physical Internet hubs and digital twin ecosystems—to support real-time, distributed, and adaptive decision-making in complex, uncertain environments (Perez et al., 2024a; Sharifmousavi et al., 2024; Walter & Mikkola, 2024). By embedding intelligence into every node, MASs redefine traditional decision support systems (DSS), which now leverage cognitive negotiation, modular simulation, and agent-based interactions to address challenges in supplier selection, logistics coordination, and production monitoring (Aslani Khiavi et al., 2024; Sahraoui & Bellaouar, 2024; Singh & Yadav, 2024). This decentralized architecture is crucial under VUCA conditions, where resilience, flexibility, and responsiveness are essential (L. Xu, Mak, Proselkov, et al., 2024; Zekhnini et al., 2024). Reinforcement learning and actor-critic models enhance decision autonomy, enabling MAS to operate within real-time systems that optimize vehicle routing, inventory control, and energy consumption (Fedorov et al., 2024; Kamta & Sharma, 2024; Patil & Nezamoddini, 2024). These developments coincide with the rise of sustainability as a central strategic goal, moving beyond environmental compliance to embed lifecycle-aware planning and emission-reduction capabilities directly into operational flows (Lehmann et al., 2023; Perez et al., 2024b; Sahraoui & Bellaouar, 2024). Information security and explainability have also gained prominence, with MAS architectures designed to ensure privacy-preserving and trustworthy decision-making processes, especially in sensitive procurement and distribution settings (Cherif et al., 2024; B. Zhang et al., 2024). Moreover, case-based reasoning and system dynamics models are now used to simulate stakeholder interactions, reflecting a broader shift toward collaborative governance in supply chains (Motsch et al., 2024; Zheng et al., 2024). Real-time control mechanisms enabled by MAS are vital in mitigating ripple effects such as the bullwhip effect, enhancing synchronization across tiers, and improving supply chain visibility (Lehmann et al., 2023; J. Li et al., 2024). Ultimately, MASs have evolved from supportive tools to central agents of transformation—embedding intelligence, sustainability, and adaptability into supply chain operations across diverse domains, including agri-food, manufacturing, urban logistics, and energy distribution (W. Chen et al., 2024; Duran et al., 2024; Song et al., 2024; Yi et al., 2024).

Despite the transformative potential of multi-agent systems (MAS) in supply chain decision-making, their widespread adoption remains constrained by a convergence of technical, organizational, and socio-economic challenges. A recurring issue is the lack of interoperability and standardization across theoretical frameworks, which inhibits the consistent deployment and scaling of MAS in real-world industrial settings (Hamou et al., 2024; Huckert et al., 2024; L. Xu, Mak, Proselkov, et al., 2024). Coordination among heterogeneous agents is particularly complex in dynamic environments, where decentralized architectures must reconcile conflicting objectives, manage stochastic disruptions, and mitigate risks like the bullwhip effect (Aslani Khiavi et al., 2024; X. Liu et al., 2024; Singh & Yadav, 2024). The opacity of advanced decision-making models—especially those based on reinforcement learning or large language models—limits explainability and trust, discouraging adoption by practitioners unfamiliar with their inner workings (Fedorov et al., 2024; X. Liu et al., 2024; L. Xu, Almahri, Mak, et al., 2024). Furthermore, despite advances in modular simulation and agent negotiation, MASs still struggle to maintain consistent performance under information asymmetries, environmental noise, and fluctuating stakeholder strategies (Duran et al., 2024; Gómez-Marín et al., 2024; Mehra, Saha, et al., 2024). Privacy and data security concerns further complicate integration, especially in cyber-physical systems and IoT-driven supply chains, where sensitive or unverified data must be exchanged among decentralized actors (Al-Shamaileh et al., 2024; Cherif et al., 2024; B. Zhang et al., 2024). High infrastructure demands—including the need for robust digital twins and unified semantic models—create additional barriers, especially for small or resource-constrained enterprises (Sahraoui & Bellaouar, 2024; H. Zhang, 2024). Many architectures remain at the simulation stage, with limited empirical validation and inconsistent transferability across sectors or regions (Attajer & Mecheri, 2024; Sahraoui et al., 2024). Moreover, while some agent-based models offer sustainability insights, they may falter under dominant market structures or misaligned incentives, revealing the limits of purely technical optimization (W. Chen et al., 2024; Zhao & Wang, 2024). The literature thus highlights a persistent tension between MAS sophistication and operational feasibility—calling for transparent, modular, and context-aware systems that bridge the gap between theory and industrial viability through more precise roadmaps, interdisciplinary coordination, and enhanced human-agent interaction.

The future of research on multi-agent systems (MAS) in supply chains lies in developing adaptive, explainable, and ethically grounded frameworks that can navigate increasing complexity and sustainability demands. A key direction involves refining hybrid decision-making architectures that combine reinforcement learning with rule-based or case-based reasoning to balance real-time adaptability and historical insight, thereby enhancing transparency and performance (Fedorov et al., 2024; Sharifmousavi et al., 2024; Song et al., 2024). As decentralized and dynamic supply chains become the norm, MAS must be co-designed with scalable cyber-physical architectures and intelligent digital twins to ensure resilience under disruption and enable feedback-driven optimization (Lehmann et al., 2023; Sahraoui et al., 2024). Emerging work also highlights the importance of consensus protocols and multi-agent coordination mechanisms for mitigating inefficiencies like the bullwhip effect, especially in systems with periodic review cycles and demand variability (Aslani Khiavi et al., 2024; Mousa et al., 2024). Parallel efforts are needed to formalize trust and reputation models in IoT-based MAS networks, leveraging decentralized identity systems and blockchain consensus to secure agent collaboration while preserving data integrity (Al-Shamaileh et al., 2024; Cherif et al., 2024). In sustainability-driven supply chains, MAS research should expand its focus to lifecycle-aware planning, quantifying emissions, waste, and resource flows while incorporating game-theoretical models to simulate policy impacts and market behavior in carbon-constrained or volatile environments (W. Chen et al., 2024; Perez et al., 2024a; Sahraoui & Bellaouar, 2024). Interdisciplinary approaches integrating behavioral economics and digital strategy are crucial to designing incentive structures that align agent autonomy with collective goals, particularly in carbon markets and underserved regions (da Silva-Ovando et al., 2024; Mehra, Saha, et al., 2024; Zheng et al., 2024). Research into fairness-aware scheduling and social equity in reverse logistics could support the rise of inclusive, human-centric supply chains (Duran et al., 2024; Jia et al., 2023). The convergence of MAS with foundation models and multi-stage optimization strategies presents new opportunities to advance explainable, multi-domain reasoning under uncertainty (X. Liu et al., 2024; L. Xu, Almahri, Mak, et al., 2024). Ultimately, these research trajectories underscore the imperative to blend system-level intelligence with ethical, contextual, and collaborative dimensions to realize the next generation of intelligent, resilient, and sustainable supply chains.

Managers and practitioners aiming to implement multi-agent systems (MAS) in supply chains should pursue a strategic, modular, and incremental integration approach, targeting early deployments in high-impact areas such as supplier selection, last-mile logistics, and inventory control (Mehra, Saha, et al., 2024; Patil & Nezamoddini, 2024; Zekhnini et al., 2024). These initial implementations can leverage agent-based decision support systems to achieve measurable cost efficiency, responsiveness, and sustainability improvements (Attajer & Mecheri, 2024; Perez et al., 2024b). Simulation-based environments, including digital twin platforms, should be used as testbeds for validating MAS behavior under varying conditions before full-scale deployment, especially in complex or modular production settings (Sahraoui et al., 2024; Sahraoui & Bellaouar, 2024). Organizational readiness can be strengthened through coordinated efforts between IT and operations teams to ensure interoperability, robust data governance, and cyber-physical integration (Kamta & Sharma, 2024; Khiloun et al., 2024; Yi et al., 2024). In parallel, attention must be paid to system transparency and explainability; MAS incorporating reinforcement learning or large language models should provide interpretable outputs and interfaces for human oversight to enhance trust and accountability in decision-making processes (Fedorov et al., 2024; Z. Li et al., 2024; Patil & Nezamoddini, 2024). Data-sensitive environments may require privacy-preserving frameworks to ensure secure information exchange without compromising coordination or policy alignment (Cherif et al., 2024; B. Zhang et al., 2024). In collaborative ecosystems, coordination contracts and agent negotiation mechanisms must be designed to balance fairness, individual agent goals, and shared performance metrics (Duran et al., 2024; Jia et al., 2023; Walter & Mikkola, 2024). Moreover, inclusive applications—such as MAS in underserved markets or nano store logistics—demonstrate the potential for agent-based systems to enhance social equity and accessibility in supply networks (da Silva-Ovando et al., 2024). Sustainable development goals should be operationalized within MAS frameworks through embedded metrics that monitor emissions, resource use, and lifecycle impacts (Khankhour et al., 2024; Perez et al., 2024a). Lastly, managers should engage with policymakers and academic stakeholders to support the co-development of standards and incentive mechanisms that guide MAS evolution toward real-world viability, ensuring alignment with organizational performance and broader societal objectives (Huckert et al., 2024; Motsch et al., 2024; Zheng et al., 2024).

## Cluster 2: Adaptive Learning Agents for Optimization

This thematic cluster reflects the rapid convergence of reinforcement learning (RL), multi-agent reinforcement learning (MARL), and heuristic-based methods with MASs to address dynamic, high-dimensional challenges in supply chain management. Across diverse applications—from vehicle routing and last-mile delivery to inventory coordination and collaborative scheduling—MAS are equipped with deep and hierarchical RL architectures that redefine distributed decision-making under uncertainty (Z. Bi et al., 2024; X. Liu et al., 2024; Wang et al., 2024; Y. Zhu et al., 2023). These systems increasingly rely on hybrid learning models that integrate heuristic strategies such as genetic algorithms, artificial bee colony optimization, and fuzzy logic to enhance performance in multi-objective, constrained environments (Dharmapriya et al., 2022; Khankhour et al., 2024; Nain & Kumar, 2022; Sara & Btissam, 2020). The scalability and adaptability of MARL-based frameworks are particularly evident in logistics scenarios such as truck scheduling, cross-docking terminals, and hydrogen supply chains, where real-time responsiveness and cooperative coordination are paramount (Chakir et al., 2020; Kusuma, 2021; Song et al., 2024). Advanced architectures like parameter-sharing deep Q-networks and transformer-enhanced communication protocols enable agents to operate autonomously while maintaining privacy and minimizing information exchange, especially in modular and decentralized platforms (Maestro et al., 2021; Ngu et al., 2022; B. Zhang et al., 2024). Social learning mechanisms and incentive negotiation models are also being integrated to align agent behavior with broader supply chain goals, including sustainability, personalization, and resilience (de Bok & Tavasszy, 2022; J.-Y. Sun et al., 2022; F. Yu et al., 2022). The growing use of multi-agent simulation environments—such as OFCOURSE and other modular digital twins—demonstrates the practical applicability of these systems for policy impact assessment and lifecycle planning in zero-emission urban logistics zones (de Bok & Tavasszy, 2022; Y. Zhu et al., 2023). As a result, this cluster marks a shift from isolated algorithmic optimization to holistic, context-aware agent ecosystems that dynamically learn, adapt and collaborate across the entire supply network. These developments position MASs as computational tools and cognitive, sustainable, and agile infrastructures capable of supporting next-generation autonomous supply chains (Z. Bi et al., 2024; Mehra, Saha, et al., 2024; T. Zhu et al., 2022).

Despite substantial progress, the deployment of reinforcement learning (RL) and multi-agent reinforcement learning (MARL) in supply chain environments continues to face interconnected challenges that limit scalability, interpretability, and operational reliability. A key obstacle is the exponential growth in planning complexity as the number of interacting agents increases, particularly in dynamic and decentralized logistics contexts where coordination overhead becomes a bottleneck (Z. Bi et al., 2024; Tarhan & Ure, 2024; Wang et al., 2024). While deep learning techniques, including deep Q-networks and transformer-based communication, offer performance improvements, they impose high computational costs and reduce interpretability—posing barriers to real-time deployment and practitioner trust (Mehra, Saha, et al., 2024; Vallecillos Ruiz, 2024; B. Zhang et al., 2024). Scalability remains constrained, especially in large-scale path-planning tasks that resemble multi-agent traveling salesman problems, where heuristic or simulation-based methods struggle with long computation times (Maktabifard et al., 2023; Ren et al., 2022). Additionally, heterogeneous agent goals, self-interest, and asymmetric information environments complicate cooperative behavior, establishing universally acceptable reward structures or fairness across agents (M. Bi et al., 2024; Dharmapriya et al., 2022; Hasan & Niyogi, 2020). Environmental uncertainties—such as demand variability, inventory disruptions, or dynamic scheduling—further undermine the convergence stability of learning agents and often require simulation-intensive validation before practical deployment (Grosset et al., 2024; X. Liu et al., 2024; Y. Zhu et al., 2023). Compounding these technical issues are broader infrastructural limitations: real-time data integration is usually hampered by legacy systems, limited data availability, and poor interoperability between enterprise platforms and simulation tools (Köhler et al., 2021; Maestro et al., 2021; Nain & Kumar, 2022). Privacy concerns impede multi-agent collaboration, as organizations may be reluctant to share operational data due to competitive risks or regulatory constraints (B. Zhang et al., 2024). Moreover, many current platforms fail to replicate the sequential and interdependent nature of supply chain tasks—such as those in collaborative inventory or closed-loop logistics—highlighting the need for custom training environments and robust control frameworks (Dabaj et al., 2021; Kusuma & Kallista, 2022; W. Xu & Dong, 2023). While RL-based MASs offer substantial theoretical advantages in distributed supply chain optimization, their real-world deployment must overcome significant computation, coordination, scalability, and system-level integration challenges to deliver their full potential (M. Bi et al., 2024; Y.-T. Chen & Cao, 2020; Nishi et al., 2024).

Future research on MASs in supply chain environments must prioritize the development of scalable, interpretable, and context-aware learning architectures that can operate under real-time constraints and high environmental variability. A central challenge lies in enhancing multi-agent reinforcement learning (MARL) frameworks to effectively balance individual agent autonomy with collective efficiency, especially in scenarios requiring dynamic coordination and long-term system-wide optimization (Z. Bi et al., 2024; Dharmapriya et al., 2022; Nishi et al., 2024). Promising directions include integrating hybrid learning models that combine reinforcement learning with evolutionary metaheuristics, such as sparrow-inspired and genetic algorithms, to improve robustness in topologically complex or demand-volatile environments (Bu, 2024; Sara & Btissam, 2020; Song et al., 2024). Transformer-based coordination models and consensus protocols offer new possibilities for communication-efficient agent systems, particularly in high-dimensional vehicle routing and last-mile delivery tasks (Ngu et al., 2022; Ren et al., 2022; Wang et al., 2024). At the same time, embedding semantic and ontological frameworks into MAS can enable knowledge-driven planning, particularly in spatially distributed problems like location-inventory-routing (Babaei et al., 2024). Including carbon-aware rewards and life cycle assessments into agent objectives may support sustainability goals across production and logistics networks (Y. Li & Wang, 2024; W. Xu & Dong, 2023; F. Yu et al., 2022). The advancement of simulation-based optimization and digital twin platforms enables scenario-driven policy testing, risk mitigation, and iterative system improvement in green and crisis logistics contexts (Chakir et al., 2020; Z. Liu et al., 2023; Matsuda et al., 2020). Future work should also deepen the modeling of agent heterogeneity to capture real-world contractual, operational, and behavioral diversity, ensuring that MAS solutions align with heterogeneous stakeholder goals (Herrera et al., 2020; Kusuma & Kallista, 2022; Maestro et al., 2021). Extending VMI-based MAS models to multi-product and multi-actor ecosystems and integrating ERP systems for operational scaling will enable adaptive, decentralized replenishment strategies (Kusuma & Kallista, 2022; Nain & Kumar, 2022). Lastly, research should explore lightweight agent architectures—including modular robotic platforms—that support task parallelism and agile decision-making in constrained physical environments, from smart manufacturing to urban consolidation zones (Y.-T. Chen & Cao, 2020; de Bok & Tavasszy, 2022; T. Zhu et al., 2022). These avenues collectively highlight the need for interdisciplinary approaches that unite systems engineering, behavioral modeling, and machine learning to build resilient, intelligent, and ethically aligned supply chain ecosystems.

For practitioners aiming to implement multi-agent reinforcement learning (MARL) and related intelligent systems in supply chains, a phased, modular approach is essential for maximizing adaptability and operational resilience. Initial deployments should focus on domains with clear cost-performance benefits, such as collaborative drone delivery, vehicle routing, and last-mile logistics, where MARL frameworks have shown superior results under dynamic and uncertain conditions (Z. Bi et al., 2024; Mehra, Saha, et al., 2024; Wang et al., 2024). Hybrid learning strategies that combine reinforcement learning with heuristics—such as genetic algorithms or simulation-based tuning—are recommended to enhance convergence speed, interpretability, and control over emergent agent behavior (Bu, 2024; Khankhour et al., 2024; Tarhan & Ure, 2024). Managers should validate learning systems through robust simulation environments that allow stress testing under inventory shocks, variable demand, or political constraints (M. Bi et al., 2024; Duran et al., 2024; X. Liu et al., 2024). Especially in sustainability-sensitive sectors, such as hydrogen or medical waste logistics, agent objectives should embed environmental metrics and support regulatory compliance through incentive negotiation and carbon-aware decision-making (Sara & Btissam, 2020; Song et al., 2024; F. Yu et al., 2022). Decision outputs must be auditable and supported by visualization tools to facilitate trustworthy deployment, enabling human oversight and intervention when needed (Sahraoui et al., 2024). Organizations should prioritize modular MAS frameworks that support incremental deployment across tasks like inventory control, collaborative scheduling, or virtual warehousing and integrate with existing ERP or cloud infrastructures to ensure scalability and real-time responsiveness (Lu et al., 2022; Maestro et al., 2021; Nain & Kumar, 2022). Practitioners are encouraged to implement privacy-preserving coordination protocols to overcome inter-organizational barriers and promote data sharing without compromising sensitive information (Dharmapriya et al., 2022; B. Zhang et al., 2024). Investment in training programs for logistics, IT, and strategy teams is also critical to building internal competencies in modeling and managing intelligent agents (Köhler et al., 2021). Finally, strategic success depends on fostering a culture of continuous learning—where agents are retrained iteratively using historical and predictive scenarios—and encouraging cross-functional collaboration and shared governance structures that support long-term technology integration and adaptive decision-making across the supply network (Herrera et al., 2020; Kusuma & Kallista, 2022; Nain & Kumar, 2022).

## Cluster 3: Cognitive Infrastructures for Decentralized Supply Chains

This thematic cluster captures the growing convergence of artificial intelligence (AI), Internet of Things (IoT), blockchain, robotics, and multi-agent systems (MAS), marking a decisive shift toward decentralized, intelligent, and adaptive supply chain ecosystems. AI—particularly in deep reinforcement learning (DRL) and multi-agent reinforcement learning (MARL)—has enabled real-time, context-aware decision-making across diverse applications such as vehicle routing, order fulfillment, inventory control, and drone-based logistics (Z. Bi et al., 2024; Mehra, Singh, et al., 2024; Song et al., 2024; Wang et al., 2024). IoT technologies contribute to seamless connectivity and real-time sensing, allowing agents to operate within hyperconnected environments that support digital twins and predictive optimization (Sharifmousavi et al., 2024; Taniguchi et al., 2024). Blockchain and smart contract infrastructures enhance these systems by embedding trust, security, and traceability into decentralized supply chain transactions, which is critical in collaborative logistics and inter-organizational coordination (Cherif et al., 2024; Covaci, 2023; B. Zhang et al., 2024). Integrating learning machines into robotics has enabled autonomous systems to handle object transportation and last-mile delivery with increased efficiency and resilience, especially within smart city and warehouse settings (Hasan & Niyogi, 2024; Song et al., 2024; T. Zhu et al., 2022). Multi-agent simulations, agent-based scheduling, and joint policy optimization underpin strategic planning in logistics networks, from hydrogen and food distribution to global e-commerce fulfillment and crisis response scenarios (Mehra, Saha, et al., 2024; Song et al., 2024; Y. Zhu et al., 2023). The rise of modular cyber-physical systems and principles from the Physical Internet further reinforces this transition by promoting flexible, scalable, and sustainable logistics configurations (Shaikh et al., 2023; Suzuki & Kraiwuttianant, 2024). In this evolving landscape, consensus-based coordination, information sharing, and stakeholder alignment are increasingly supported by ontological reasoning, privacy-preserving protocols, and explainable decision models (Babaei et al., 2024; Z. Li et al., 2024; B. Zhang et al., 2024). This cluster reflects a systemic transformation of supply chains into self-organizing, cyber-physical ecosystems where MASs function as the cognitive and operational core—enabling responsiveness, personalization, and sustainability across interconnected global networks.

Despite the significant advances in integrating artificial intelligence (AI), Internet of Things (IoT), blockchain, and multi-agent systems (MAS) into supply chain operations, a range of critical challenges continues to limit their scalable and trustworthy implementation. Chief among these is the persistent issue of data interoperability, where the lack of standardized protocols across IoT platforms and legacy systems impedes seamless communication among agents and stakeholders (Sharifmousavi et al., 2024; Taniguchi et al., 2024). This is compounded by privacy and security concerns, particularly in decentralized environments using blockchain or reinforcement learning, where sensitive data and smart contract logic may be exposed to unauthorized access (Cherif et al., 2024; B. Zhang et al., 2023, 2024). While multi-agent reinforcement learning (MARL) has demonstrated strong potential in optimizing logistics operations, its application is often constrained by computational complexity, including the combinatorial explosion of decision variables and high-dimensional policy spaces (Nishi et al., 2024; Shi et al., 2023; Shu et al., 2024). Additionally, current MARL algorithms face interpretability issues, functioning as black boxes that hinder strategic transparency and stakeholder trust (Hasan & Niyogi, 2024; Khirwar et al., 2023; Tarhan & Ure, 2024). The challenge of coordinating decentralized agents becomes more acute in real-time, data-constrained scenarios—such as last-mile delivery or pandemic response—where delays or misalignments in information sharing can lead to inefficiencies, stockouts, or system collapse (Mehra, Singh, et al., 2024; Okada et al., 2023). Heuristic-based or static agent behaviors often fail to adapt to novel disruptions or dynamic consumer preferences, especially in dual-channel and cross-firm systems (Shu et al., 2024; H. Sun et al., 2023). Organizational and technical fragmentation further exacerbates these limitations, as many enterprises lack the ICT maturity and standardized architectures needed to support dynamic inventory routing, collaborative robotics, or virtual supply chain formation (Babaei et al., 2024; Hasan & Niyogi, 2024; Singh Nain & Kumar, 2023). Even where simulations demonstrate promising results—such as in cooperative inventory games or urban freight optimization—strategic misalignments among stakeholders challenge real-world deployment, ethical concerns regarding human-agent collaboration, and the absence of robust reward design aligned with system-wide objectives (Covaci, 2023; Tajima et al., 2023), these persistent barriers highlight the urgent need for hybrid frameworks that combine learning algorithms with explainable AI, enforce privacy-preserving coordination, and align stakeholder incentives to achieve resilient, scalable, and ethical multi-agent supply chain systems.

Future research must prioritize hybrid, explainable, and scalable architectures that integrate AI, IoT, and blockchain to address persistent technical and operational limitations. A promising direction lies in designing explainable AI systems by combining symbolic reasoning, model-checking, and neural architectures to enhance transparency and traceability in decision-making, particularly in logistics and production-critical contexts (Hasan & Niyogi, 2024; Z. Li et al., 2024; Sharifmousavi et al., 2024). To scale decentralized operations, lightweight blockchain protocols and privacy-preserving smart contracts must be developed to enable fast, secure coordination without compromising sensitive data (Cherif et al., 2024; B. Zhang et al., 2024). Simulation environments such as OFCOURSE should be standardized to benchmark MAS coordination strategies across sectors, fostering reproducibility and methodological alignment (Y. Zhu et al., 2023). Integrating multi-agent microsimulation with real-time IoT and energy-aware models at the urban logistics level offers a robust foundation for sustainable city planning and last-mile delivery systems (Gómez-Marín et al., 2024; Shu et al., 2024). Research must also advance stakeholder-sensitive consensus algorithms and subgradient-based optimization methods to coordinate agents efficiently under multi-objective constraints and negotiation dynamics (Miyajima & Fujita, 2024; Nishi et al., 2024). Embedding ethical reasoning and fairness constraints into smart contracts can ensure compliance and equity in collaborative, blockchain-governed networks (Sharifmousavi et al., 2024). In volatile environments such as healthcare and public safety logistics, MAS must be extended to support multi-stage adaptive inventory strategies and emergency response planning, where decentralized resilience and local autonomy are critical (Khirwar et al., 2023; Okada et al., 2023). Moreover, incorporating learning-based digital twins at both strategic and operational levels can provide real-time feedback and predictive insight, enabling proactive policy adjustments and resource planning (Taniguchi et al., 2024). Domain-specific ontological frameworks should be leveraged to support agent specialization and cross-domain generalization, particularly in emerging circular supply models and hydrogen logistics (Babaei et al., 2024; Song et al., 2024). As city-scale MAS frameworks expand, future efforts must address latency, energy efficiency, and multi-UAS coordination in air mobility logistics, ensuring responsiveness under constrained bandwidth and dense urban conditions (Jo et al., 2023; Rosenberger et al., 2022). These multifaceted directions collectively support the development of robust, intelligent, and trustworthy MAS ecosystems that are ethically aligned, operationally resilient, and capable of transforming digital supply chain infrastructures.

Managers aiming to lead the digital transformation of supply chains through MASs should prioritize modular, interoperable, and decentralized architectures that integrate artificial intelligence (AI), Internet of Things (IoT), and blockchain technologies. Initial implementations should target high-impact domains such as last-mile logistics, inventory control, and warehouse robotics. MASs have significantly improved responsiveness, cost-efficiency, and service quality through learning-based coordination (Z. Bi et al., 2024; Saha & Rathore, 2024; K. Zhang et al., 2023). Organizations must adopt interoperable platforms with standardized semantic data models that enable seamless agent communication and compatibility across legacy systems to ensure scalability and system-wide integration (Sharifmousavi et al., 2024; Singh Nain & Kumar, 2023). Simulation environments like OFCOURSE should be employed to train and validate MAS solutions under realistic, volatile conditions before deployment (Jo et al., 2023; Y. Zhu et al., 2023). In decentralized settings, privacy-preserving smart contracts and auditable coordination protocols are essential to secure stakeholder trust and data confidentiality, especially in cross-organizational networks (Cherif et al., 2024; B. Zhang et al., 2024). Managers should invest in digital twins and IoT-integrated platforms to enhance real-time monitoring and adaptive control in logistics operations (Taniguchi et al., 2024; Wang et al., 2024). Integrating reinforcement learning with energy-aware optimization models can support sustainability goals, particularly drone deliveries and electric vehicle routing (Khankhour et al., 2024; Shu et al., 2024). MASs frameworks should support shared reward mechanisms and incentive-aligned policies to mitigate the bullwhip effect and optimize cooperation across depots, suppliers, and retailers (Khirwar et al., 2023; X. Liu et al., 2024). In crisis scenarios, decentralized inventory models and autonomous technologies like modular containers and smart dispensers can enhance resilience and reduce human workload (Okada et al., 2023; Shaikh et al., 2023). Practitioners are encouraged to build cross-functional teams and foster a culture of inter-organizational collaboration, aligning data science, operations, and cybersecurity expertise to support continuous learning and iterative improvement (Hasan & Niyogi, 2024; Tajima et al., 2023). Long-term strategies should include investments in blockchain infrastructure for autonomous contracting and negotiation, enabling utility-maximizing behavior in MAS ecosystems governed with minimal central oversight (Covaci, 2023). These integrated approaches, grounded in the latest research, provide a roadmap for organizations seeking to build intelligent, adaptive, and sustainable supply chain infrastructures.

## Cluster 4: Resilient Intelligence in Distributed Supply Chains

This thematic cluster highlights the convergence of MASs, AI, and stochastic modeling as foundational enablers of resilience in modern supply chain networks. In response to rising disruption risks—from geopolitical tensions to pandemic-induced shocks—MAS architectures are increasingly employed to support decentralized decision-making, dynamic coordination, and adaptive response mechanisms across distributed environments (Lehmann et al., 2023; Sharifmousavi et al., 2024; L. Xu et al., 2023). These systems often incorporate reinforcement learning, soft computing methods, and stochastic models such as semi-Markov decision processes to enhance performance under uncertainty and to manage complex, non-linear demand patterns (Nain & Kumar, 2022; Saha & Rathore, 2024; Wang et al., 2022). AI-driven agents, supported by neural networks and large language models, enable real-time sensing, predictive routing, and linguistic translation for agent communication, extending MAS capabilities into last-mile logistics and digitally connected retail ecosystems (Fedorov & Nechyporenko, 2022; Fonseca-Galindo et al., 2022; Z. Li et al., 2024). Intelligent digital twins and goal-seeking agents have emerged as critical tools for simulation-based planning and adaptive control, particularly in environments requiring rapid reconfiguration, such as healthcare, hydrogen, and vaccine supply chains (Lehmann et al., 2023; Okada et al., 2023; Song et al., 2024). Blockchain integration further enhances these systems by introducing transparent, traceable, and contractually enforceable agent interactions, ensuring stakeholder alignment and data integrity in volatile scenarios (J. Li et al., 2024; Swain & Patra, 2022, 2024a). Recent innovations also explore hybrid systems, including neutrosophic logic and graph neural networks, to improve anomaly detection, robustness, and cooperative decision-making under complex risk conditions (Meziani et al., 2023; Protogerou et al., 2021). Resilience in this context is redefined as a systemic attribute—facilitated by agent autonomy, intelligent learning frameworks, and real-time adaptation—capable of maintaining continuity and strategic flexibility across physical and virtual supply networks (Hamou et al., 2024; Rezaei & Behnamian, 2022; L. Xu, Mak, Minaricova, et al., 2024). These developments collectively mark a shift toward resilient-by-design supply chains built on distributed intelligence, operational transparency, and data-driven situational awareness that empower systems to recover from disruptions, mitigate risk, and sustain long-term performance proactively.

Despite the rapid evolution of multi-agent systems (MAS), artificial intelligence (AI), and intelligent coordination frameworks in supply chain resilience, numerous barriers limit operational scalability, interpretability, and strategic impact. A persistent challenge lies in the lack of standardized, generalizable frameworks for implementing autonomous and decentralized supply chains across diverse industrial contexts, often resulting in fragmented and simulation-bound solutions (Nitsche et al., 2023; L. Xu et al., 2023; L. Xu, Mak, Proselkov, et al., 2024). Integrating MAS in real-world scenarios is further complicated by data asymmetries, network heterogeneity, and inconsistent digitization across supply chain tiers, which hinder agent synchronization and increase coordination costs (Dharmapriya et al., 2022; Sharifmousavi et al., 2024; Yi et al., 2024). Reinforcement learning and neural-based approaches offer promising adaptability under uncertainty. Still, their computational complexity, sensitivity to stochastic disturbances, and reliance on large-scale training data restrict their real-time applicability in domains such as hospital logistics or energy systems (Z. Liu et al., 2022; Saha & Rathore, 2024; Song et al., 2024). Moreover, current MAS frameworks often prioritize response and recovery phases while neglecting long-term resilience-building and strategic foresight, limiting their contribution to sustained supply chain evolution (Kassa et al., 2023). Privacy-preserving coordination remains a critical barrier, as concerns over data confidentiality and the lack of robust incentive mechanisms for equitable participation frequently inhibit inter-firm collaboration (Kim et al., 2024; Raju et al., 2023; B. Zhang et al., 2024). While innovations such as fictitious agents, fault-tolerant control, and digital twins have been proposed, their scalability and robustness under nonlinear, multi-echelon, and rapidly fluctuating conditions remain under-validated (Lehmann et al., 2023; Mousa et al., 2024; T.-C. Sun et al., 2022). Advanced modeling techniques—including neutrosophic logic, category theory, and soft computing hybrids—add conceptual rigor but introduce interpretability and integration challenges, particularly in enterprise-grade systems (Boudjidj et al., 2021; Meziani et al., 2023). Additionally, most MAS still lack semantic reasoning capabilities and ontological alignment, limiting their adaptability to dynamic contexts and heterogeneous stakeholder goals (Babaei et al., 2024; Fedorov & Nechyporenko, 2022). These issues underscore the gap between the theoretical potential of distributed intelligence and the practical complexities of supply chain implementation, emphasizing the need for hybrid, transparent, and domain-adaptive MAS architectures capable of balancing autonomy, coordination, and resilience under real-world constraints.

Future research on multi-agent systems in supply chains should prioritize the development of hybrid, interpretable, and socially responsive architectures that enhance resilience, coordination, and strategic foresight under disruption. A key direction involves integrating symbolic, neural, and heuristic reasoning within agent-based systems to improve scalability and decision transparency in volatile environments (Sharifmousavi et al., 2024; L. Xu, Mak, Proselkov, et al., 2024). Hybrid reinforcement learning models, especially those tailored for semi-real-time contexts, can potentially manage complexity in high-stakes domains like energy and healthcare logistics (Saha & Rathore, 2024; Song et al., 2024). Advances in digital twins—augmented with autonomous agent capabilities—can support predictive analytics and real-time risk planning, enabling supply chains to simulate, assess, and adapt to diverse disruption scenarios (Lehmann et al., 2023; L. Xu et al., 2023). The design of intelligent agents should also incorporate graph neural networks and linguistic models to enhance multilingual communication, inter-agent understanding, and cross-domain transferability in global supply systems (Fedorov & Nechyporenko, 2022, 2023). From a structural perspective, resilient systems must include mechanisms for fixed-time consensus, anomaly detection, and fault tolerance, especially in decentralized, heterogeneous networks with incomplete data or unreliable communication channels (Z. Liu et al., 2022; T.-C. Sun et al., 2022; S. Yang et al., 2022). Integrating blockchain and smart contracts with MAS opens new pathways for tamper-proof, verifiable coordination and automated compliance in distributed logistics (Swain & Patra, 2022, 2024a). Future work should explore economic and social dimensions of resilience, including the impact of agent behavior on carbon policies, local welfare, and informal economies such as nanostores (da Silva-Ovando et al., 2024; J. Li et al., 2024; Raju et al., 2023). Ontological reasoning and formal semantic modeling can improve MAS interoperability and domain adaptability. At the same time, evolutionary game theory and stakeholder-specific incentive mechanisms may align agent strategies across fragmented supply ecosystems (Babaei et al., 2024; M. Bi et al., 2024; Yi et al., 2024). Finally, research should address the limited generalizability of current frameworks by benchmarking adaptive MAS under diverse disruption types, supply chain configurations, and stakeholder preferences, ultimately supporting the design of robust, transparent, and ethically aligned supply chain intelligence (Shi et al., 2023; L. Xu, Almahri, Mak, et al., 2024; Zheng et al., 2024).

Managers seeking to develop resilient and intelligent supply chain systems should adopt a modular and incremental approach to integrating multi-agent systems, emphasizing adaptability, interoperability, and transparency. Initial deployment should focus on critical nodes—such as supplier selection, transshipment hubs, and decentralized inventory management—where MAS have effectively managed disruptions and aligned local decisions with system-wide performance goals (Dharmapriya et al., 2022; Kim et al., 2024; Zekhnini et al., 2024). Simulation-based validation and digital twins should be employed to assess MAS performance under variable demand and disruption scenarios. This allows for scenario-driven testing of agent strategies and predictive risk planning (Lehmann et al., 2023; L. Xu et al., 2023; L. Xu, Mak, Minaricova, et al., 2024). In parallel, managers should invest in blockchain-enabled smart contracts and modular infrastructure (e.g., vision sensors, smart containers) to improve coordination, trust, and operational resilience in distributed environments such as prefabricated assembly or last-mile delivery (J. Li et al., 2024; Shaikh et al., 2023; Swain & Patra, 2022). Knowledge-sharing ontologies and semantic reasoning frameworks must be prioritized to support cross-functional and cross-organizational collaboration, particularly in logistics, planning, and risk management (Babaei et al., 2024; Yi et al., 2024). For decentralized networks, firms should implement partial information-sharing mechanisms that preserve data privacy while enabling coordination among autonomous agents, reducing transaction costs, and improving responsiveness (M. Bi et al., 2024; Sharifmousavi et al., 2024). Managers in high-risk or regulated sectors (e.g., public health, energy) should explore using interpretable AI models and reinforcement learning agents designed for semi-Markov or hierarchical decision-making under uncertainty (Saha & Rathore, 2024; Song et al., 2024; L. Xu, Almahri, Mak, et al., 2024). Risk-aware planning should integrate agent-based simulations of economic behavior—such as lead-time sensitivity and pricing dynamics—to support agile responses in dual-channel systems and underserved retail markets (da Silva-Ovando et al., 2024; Raju et al., 2023). Advanced capabilities such as graph-based anomaly detection and real-time consensus mechanisms should be adopted to ensure system reliability and robustness under stochastic or adversarial conditions (Z. Liu et al., 2022; Protogerou et al., 2021). Ultimately, fostering a culture of innovation and computational experimentation, alongside the strategic deployment of hybrid MAS architectures, will enable firms to transition from reactive disruption management to proactive, intelligent supply chain orchestration in increasingly complex and uncertain global ecosystems (Meziani et al., 2023; Nitsche et al., 2023; S. Yang et al., 2022).

## Cluster 5: Intelligent Optimization for Last-Mile Logistics

This thematic cluster captures the convergence of multi-agent systems, heuristic and metaheuristic optimization, and intelligent decision-making models in addressing the increasing complexity of logistics and last-mile delivery in supply chains. Central to this evolution is the shift from centralized, static optimization methods to distributed, learning-enabled architectures capable of real-time decision-making under uncertainty. MAS integrated with mixed integer linear programming (MILP), genetic algorithms, and reinforcement learning are applied to resolve dynamic resource allocation, delivery routing, and scheduling challenges in high-dimensional, decentralized environments (Fedorov et al., 2024; Khankhour et al., 2024; Tarhan & Ure, 2024). These systems capture modern logistics’ stochastic, heterogeneous nature, particularly in urban and last-mile contexts, where customer behavior, demand variability, and spatial constraints pose substantial challenges (Bounadi et al., 2023; Fedorov et al., 2024; Fonseca-Galindo et al., 2022). Hybrid frameworks, such as genetic algorithm-aided reinforcement learning and swarm-inspired scheduling agents, have effectively scaled aerial drone deliveries and mitigated planning space complexity (Bu, 2024; Gaida et al., 2023; Tarhan & Ure, 2024). Simultaneously, agent-based models are employed in multimodal hub optimization, collaborative scheduling, and waste reduction, reflecting a broader trend toward sustainable, system-wide efficiency gains under the physical internet paradigm (Duran et al., 2024; Nguyen et al., 2023; Perez et al., 2024a). These MAS-based architectures support real-time adaptation through simulation-based validation, allowing them to respond to disruption while aligning local agent behavior with global supply chain objectives (Gómez-Marín et al., 2024; Y. Zhu et al., 2023). Moreover, integrating ontological models and trust-driven agent negotiation mechanisms in smart factory environments reinforces the need for transparency, performance reliability, and semantic interoperability in distributed systems (Al-Shamaileh et al., 2024; Babaei et al., 2024). As organizations transition toward intelligent, modular logistics ecosystems, MAS are increasingly leveraged to optimize immediate operational outcomes and orchestrate long-term strategic coordination across supply chain tiers and digital infrastructures. This reflects a paradigm shift from isolated optimization modules to intelligent, collaborative ecosystems where agents dynamically negotiate, adapt, and optimize within and across interconnected logistics networks (Dusadeerungsikul et al., 2022; Y. Liu et al., 2023; Walter & Mikkola, 2024).

Despite significant advances, the deployment of optimization-enhanced MASs in supply chain logistics—particularly in last-mile delivery—continues to face critical challenges related to scalability, robustness, and real-world applicability. Central to these limitations is the computational intensity of solving large-scale mixed integer programming problems and executing real-time heuristic or metaheuristic evaluations under stochastic demand and high-frequency decision updates (Arishi & Krishnan, 2023; Rezaei & Behnamian, 2022; Tarhan & Ure, 2024). While MAS architectures offer potential for decentralized, adaptive planning, they often struggle to achieve global coordination due to fragmented agent objectives and limited mechanisms for reconciling local utility with system-wide optimization (Deshmukh et al., 2023b; Fedorov et al., 2024). Agent-based models that perform well in simulation environments like OFCOURSE or digital twins frequently encounter performance degradation when exposed to real-time disruptions, dynamic customer behavior, and infrastructure constraints not fully captured in training scenarios (Fonseca-Galindo et al., 2022; Gómez-Marín et al., 2024; Y. Zhu et al., 2023). Additionally, most optimization frameworks rely on deterministic or complete information assumptions, undermining their effectiveness in volatile, uncertain, complex, and ambiguous (VUCA) environments (Hamou et al., 2024; H. Sun et al., 2023). This is further exacerbated in dual-channel logistics systems where the balance between decentralized autonomy and centralized oversight remains challenging to maintain (H. Sun et al., 2023; Suzuki & Kraiwuttianant, 2024). The integration of responsible autonomy—ensuring agents align self-interested actions with collective goals—remains underdeveloped, posing ethical and operational challenges in high-stakes domains such as vaccine distribution and modular manufacturing (Deshmukh & Srinivasa, 2022; Okada et al., 2023; T. Zhu et al., 2022). Moreover, many current approaches overlook broader societal or sustainability metrics, such as carbon emissions or local economic impact, thereby limiting their alignment with emerging environmental and social governance (ESG) expectations (Khankhour et al., 2024; Shaikh et al., 2023). Despite the theoretical appeal of multi-agent negotiation frameworks and biologically inspired algorithms (e.g., ant colony optimization), their robustness in real-time applications is not yet proven across heterogeneous industrial settings (Gaida et al., 2023; Y. Liu et al., 2023). Lastly, the absence of standardized simulation platforms and protocol interoperability hinders benchmarking and cross-domain deployment, highlighting a pressing need for unified methodological foundations that support resilient, scalable, and ethically aligned MAS optimization across diverse supply chain environments (Babaei et al., 2024; Nitsche et al., 2023; Swain & Patra, 2024b).

Future research in this cluster should prioritize the development of hybrid optimization architectures that enhance the scalability, robustness, and interpretability of multi-agent systems in dynamic and uncertain logistics environments. A key opportunity lies in combining mixed-integer programming and heuristic search methods with reinforcement learning, allowing systems to exploit structural regularities while adapting to stochastic disruptions through experiential learning (Bu, 2024; Khankhour et al., 2024; Tarhan & Ure, 2024). Such hybridization can also support metaheuristic tuning, enabling agents to modify optimization parameters in response to changing demand patterns or operational constraints (Duran et al., 2024; Gaida et al., 2023). Integrating environmental sustainability into multi-objective models remains essential, especially for last-mile delivery and physical internet applications where emission reduction, space utilization, and service equity are critical considerations (Perez et al., 2024b, 2024a). At the systems level, deploying agent-based digital twins linked to sensor-driven data streams and real-time simulations presents a promising path for predictive disruption planning and adaptive resource allocation (Gómez-Marín et al., 2024; Lehmann et al., 2023). Blockchain-enabled smart contracts can further enhance coordination, transparency, and security, particularly in decentralized networks where trust and traceability are prerequisites for autonomous execution (Cherif et al., 2024; Swain & Patra, 2024b). To improve system-wide performance, research should advance shared-reward cooperative mechanisms and multi-agent consensus models, which align individual agent incentives with global supply chain goals even under decentralized or adversarial conditions (Deshmukh et al., 2023b; Y. Zhu et al., 2023). Explainability remains a critical concern; therefore, optimization frameworks should evolve to include decision transparency features that allow human managers to audit, interpret, and intervene in agent behavior when necessary (Deshmukh & Srinivasa, 2022; Fedorov et al., 2024). Finally, the design of interoperable and ontology-driven knowledge systems will support the generalization of MAS optimization strategies across domains. At the same time, standardized benchmarking platforms will enable comparative validation under realistic, high-stakes logistics scenarios (Babaei et al., 2024; Bounadi et al., 2023; H. Sun et al., 2023). These directions offer a research agenda for building intelligent, resilient, and ethically aligned supply chain ecosystems driven by advanced optimization and multi-agent collaboration.

Managers aiming to implement optimization-enhanced MASs in supply chains should begin by identifying critical operational bottlenecks where combinatorial complexity, time sensitivity, or fluctuating demand justifies the use of advanced modeling approaches, such as vehicle routing, delivery sequencing, and cross-docking scheduling (Bu, 2024; Duran et al., 2024; Tarhan & Ure, 2024). Integrating hybrid optimization models—combining heuristic methods like genetic algorithms with exact approaches such as mixed integer linear programming or reinforcement learning—can significantly improve solution quality, convergence, and adaptability in dynamic logistics environments (Arishi & Krishnan, 2023; Khankhour et al., 2024). Practitioners should invest in agent-based simulation environments to stress-test optimization policies under stochastic demand and disruption scenarios, ensuring robustness before real-world deployment (Gómez-Marín et al., 2024; Icarte-Ahumada & Riveros, 2023). In last-mile delivery, co-developing optimization models with real-time data feeds allows agents to adapt decisions based on traffic conditions, resource availability, and customer constraints, enhancing responsiveness and service quality (Fonseca-Galindo et al., 2022; Vijay et al., 2024). Modular MAS architectures and interoperability protocols support integration across decision support tools, enabling seamless coordination among agents and subsystems (Babaei et al., 2024; Dusadeerungsikul et al., 2022). Blockchain-enabled platforms and smart contracts should be explored to ensure transparency, traceability, and privacy in decentralized environments, particularly in manufacturing and multi-tier supplier networks (Cherif et al., 2024; Swain & Patra, 2024b). Supply chain leaders should promote cross-functional collaboration between logistics professionals, AI specialists, and operations researchers to ensure that optimization frameworks are technically rigorous and operationally viable (Fedorov et al., 2024; Iskierka et al., 2024). Training programs focused on AI, optimization, and distributed systems are essential to successfully equip teams to adopt and manage intelligent agent platforms (Radisic-Aberger et al., 2022). Ethical considerations, including fairness and responsible AI behavior, should be embedded in optimization models to build stakeholder trust and ensure long-term sustainability, especially in autonomous decision-making scenarios (Deshmukh et al., 2023a; Deshmukh & Srinivasa, 2022). Finally, decision-makers must ensure that optimization results align with strategic key performance indicators—cost, resilience, service level, and sustainability—so that local agent actions collectively support network-wide efficiency and value creation (Deshmukh et al., 2023b; Perez et al., 2024b).

# Conclusions

This review has systematically mapped the thematic landscape of multi-agent systems in supply chain management through a data-driven analysis of 437 Scopus-indexed documents. The study identifies five dominant thematic clusters—from distributed optimization and intelligent logistics to adaptive decision-making and sustainable operations—demonstrating that MASs have moved from conceptual experimentation to increasingly practical and strategic implementation. These systems enable decentralized, real-time coordination among heterogeneous actors and processes, offering flexible and scalable solutions for dynamic logistics challenges such as last-mile delivery, inventory control, and urban freight planning.

The findings confirm that MAS architectures are well aligned with the core objectives of production research: improving system responsiveness, enhancing resource utilization, and supporting decision-making under uncertainty. Integrating MAS with heuristic optimization, mixed-integer programming, reinforcement learning, and digital twins represents a key trajectory for advancing operational efficiency and strategic resilience. Moreover, adopting ontological models, privacy-preserving protocols, and smart contracts reflects a growing concern for semantic interoperability, trust, and transparency in multi-agent environments.

However, critical challenges persist. These include the lack of standardized modeling frameworks, limited real-world scalability, interpretability issues in deep learning-based MAS, and ethical concerns in autonomous decision-making. The gap between simulation and deployment underscores the need for more robust benchmarking, improved agent coordination protocols, and context-aware hybrid architectures. Efforts to align MAS outputs with organizational KPIs such as cost efficiency, service quality, and environmental sustainability remain underdeveloped.

This review contributes to production and operations management by offering a structured and comprehensive synthesis of MAS research in supply chains. It identifies what has been achieved and what remains to be addressed so that MAS can fulfill its potential as a core component of intelligent supply chain ecosystems. Future research should prioritize hybrid, explainable, and ethically aligned MAS architectures capable of managing complexity while supporting strategic foresight, operational flexibility, and sustainable value creation. By doing so, MAS can become an integral enabler of the digital transformation of production and logistics systems.

# References

Achatbi, I., Amechnoue, K., Haddadi, T. E. L., & Allouch, S. A. (2020). Advanced system based on ontology and multi agent technology to handle upstream supply chain: Intelligent negotiation protocol for supplier and transportation provider selection. *Decision Science Letters*, *9*(3), 337-354. Scopus. https://doi.org/10.5267/j.dsl.2020.5.002

Al-Shamaileh, M., Anthony, P., & Charters, S. (2024). Agent-Based Trust and Reputation Model in Smart IoT Environments. *Technologies*, *12*(11). Scopus. https://doi.org/10.3390/technologies12110208

Aria, M., & Cuccurullo, C. (2017). bibliometrix: An R-tool for comprehensive science mapping analysis. *Journal of Informetrics*, *11*(4), 959-975. https://doi.org/10.1016/j.joi.2017.08.007

Arishi, A., & Krishnan, K. (2023). A multi-agent deep reinforcement learning approach for solving the multi-depot vehicle routing problem. *Journal of Management Analytics*, *10*(3), 493-515. Scopus. https://doi.org/10.1080/23270012.2023.2229842

Aslani Khiavi, S., Jafari-Nadoushan, M., & Khankalantary, S. (2024). Multi-agent control of periodic-review supply chain. *Production Engineering*, *18*(5), 863-874. Scopus. https://doi.org/10.1007/s11740-024-01277-z

Attajer, A., & Mecheri, B. (2024). Multi-Agent Simulation Approach for Modular Integrated Construction Supply Chain. *Applied Sciences (Switzerland)*, *14*(12). Scopus. https://doi.org/10.3390/app14125286

Babaei, F., Boozarjomehry, R. B., Ravandi, Z. K., & Pishvaie, M. R. (2024). Enabling digital transformation of dynamic location-inventory-routing optimization in natural gas-to-product and energy networks via a domain-adaptable ontological agent-based framework. *Advanced Engineering Informatics*, *60*. Scopus. https://doi.org/10.1016/j.aei.2024.102380

Baena, B., Cobian, C., Larios, V. M., Orizaga, J. A., MacIel, R., Cisneros, M. P., & Beltran-Ramirez, J. R. (2020). *Adapting food supply chains in Smart Cities to address the impacts of COVID19 a case study from Guadalajara metropolitan area*. 2020 IEEE International Smart Cities Conference, ISC2 2020. Scopus. https://doi.org/10.1109/ISC251055.2020.9239076

Bala, R., Kumar, A., & Nain, P. K. S. (2024). *Multi-Agent Based Smart System for Supply Chain Management*. 1482-1486. Scopus. https://doi.org/10.1109/IC2PCT60090.2024.10486294

Bi, M., Estrada-Garcia, J.-A., Tilbury, D. M., Shen, S., & Barton, K. (2024). Heterogeneous Risk Management Using a Multi-Agent Framework for Supply Chain Disruption Response. *IEEE Robotics and Automation Letters*, *9*(6), 5126-5133. Scopus. https://doi.org/10.1109/LRA.2024.3388838

Bi, Z., Guo, X., Wang, J., Qin, S., & Liu, G. (2024). Truck-Drone Delivery Optimization Based on Multi-Agent Reinforcement Learning. *Drones*, *8*(1). Scopus. https://doi.org/10.3390/drones8010027

Boudjidj, A., Merah, E., & El Habib Souidi, M. (2021). Towards a formal multi-agent organizational modeling framework based on category theory. *Informatica (Slovenia)*, *45*(2), 277-288. Scopus. https://doi.org/10.31449/inf.v45i2.2967

Bounadi, N., Boussalia, S. R., & Bellaouar, A. (2023). Optimizing Algerian Company’s Delivery Fleet with Agent\_Based Model in Anylogic. *Transport and Telecommunication*, *24*(4), 434-442. Scopus. https://doi.org/10.2478/ttj-2023-0034

Bu, L. (2024). Logistic Resource Allocation Based on Multi-Agent Supply Chain Scheduling Using Meta-Heuristic Optimization Algorithms. *Applied Artificial Intelligence*, *38*(1). Scopus. https://doi.org/10.1080/08839514.2024.2362516

Chakir, I., El Khaili, M., & Mestari, M. (2020). *Logistics flow optimization for advanced management of the crisis situation*. *175*, 419-426. Scopus. https://doi.org/10.1016/j.procs.2020.07.059

Chen, C., & Xu, C. (2018). A Negotiation Optimization Strategy of Collaborative Procurement with Supply Chain Based on Multi-Agent System. *Mathematical Problems in Engineering*, *2018*. Scopus. https://doi.org/10.1155/2018/4653648

Chen, W., Cui, M., Quayson, M., & Du, H. (2024). Price and carbon emission reduction technology competition in the electricity supply chain based on power structure. *RAIRO - Operations Research*, *58*(5), 4621-4650. Scopus. https://doi.org/10.1051/ro/2024180

Chen, Y.-T., & Cao, Z.-C. (2020). An investigation on a closed-loop supply chain of product recycling using a multi-agent and priority based genetic algorithm approach. *Mathematics*, *8*(6). Scopus. https://doi.org/10.3390/MATH8060888

Cherif, A. N., Youssfi, M., En-Naiman, Z., Tadlaou, A., Soulami, M., & Bouattane, O. (2024). CQRS and Blockchain with Zero-Knowledge Proofs for Secure Multi-Agent Decision-Making. *International Journal of Advanced Computer Science and Applications*, *15*(11), 892-907. Scopus. https://doi.org/10.14569/IJACSA.2024.0151188

Courseault Trumbach, C., & Payne, D. (2007). Identifying synonymous concepts in preparation for technology mining. *Journal of Information Science*, *33*(6), 660-677.

Covaci, F. L. (2023). Enabling the smart supply chain ecosystems: A multi-parameter decentralized model for Supply Chain 5.0. *Journal of Computational Science*, *71*. Scopus. https://doi.org/10.1016/j.jocs.2023.102040

da Silva-Ovando, A. C., Mejía, G., Mejía-Argueta, C., Rivera, D. G., Quiroz, D. N. Y., & Chong, M. (2024). Simulating continuance and resilience: An agent-based model for nanostores operations. *Production*, *34*. Scopus. https://doi.org/10.1590/0103-6513.20230092

Dabaj, F. Z., Aoura, Y., Ouzizi, L., Douimi, M., & Nachour, A. (2021). *Dynamic planning integrated to production and maintenance in composites industry: Application of mase methodology*. 7055-7066. Scopus. https://www.scopus.com/inward/record.uri?eid=2-s2.0-85114247431&partnerID=40&md5=e1c7b5d8746fc10da43c70ca4d2f2c41

Darbari, M., & Ahmad, H. (2019). *Application of multi agent system in supply chain for e-products of government with special reference to government e-marketplace*. ACM International Conference Proceeding Series. Scopus. https://doi.org/10.1145/3339311.3339321

de Bok, M., & Tavasszy, L. (2022). Application of an empirical multi-agent model for urban goods transport to analyze impacts of zero emission zones in The Netherlands. *Transport Policy*, *124*, 119-127. Scopus. https://doi.org/10.1016/j.tranpol.2020.07.010

Deshmukh, J., Adivi, N., & Srinivasa, S. (2023a). *Modeling Application Scenarios for Responsible Autonomy using Computational Transcendence*. *2023-May*, 2496-2498. Scopus. https://www.scopus.com/inward/record.uri?eid=2-s2.0-85171293559&partnerID=40&md5=dc6ccc9e8b60f4555812b0cfc4432081

Deshmukh, J., Adivi, N., & Srinivasa, S. (2023b). *Resolving the Dilemma of Responsibility in Multi-agent Flow Networks*. *13955 LNAI*, 76-87. Scopus. https://doi.org/10.1007/978-3-031-37616-0\_7

Deshmukh, J., & Srinivasa, S. (2022). Computational Transcendence: Responsibility and agency. *Frontiers in Robotics and AI*, *9*. Scopus. https://doi.org/10.3389/frobt.2022.977303

Dharmapriya, S., Kiridena, S., & Shukla, N. (2022). Multiagent Optimization Approach to Supply Network Configuration Problems With Varied Product-Market Profiles. *IEEE Transactions on Engineering Management*, *69*(6), 2707-2722. Scopus. https://doi.org/10.1109/TEM.2019.2950694

Dominguez, R., & Cannella, S. (2020). Insights on multi-agent systems applications for supply chain management. *Sustainability (Switzerland)*, *12*(5), 1-13. Scopus. https://doi.org/10.3390/su12051935

Donthu, N., Kumar, S., Mukherjee, D., Pandey, N., & Lim, W. M. (2021). How to conduct a bibliometric analysis: An overview and guidelines. *Journal of Business Research*, *133*, 285-296. https://doi.org/10.1016/j.jbusres.2021.04.070

Du, J., Sugumaran, V., & Gao, B. (2017). RFID and multi-agent based architecture for information sharing in prefabricated component supply chain. *IEEE Access*, *5*, 4132-4139. Scopus. https://doi.org/10.1109/ACCESS.2017.2665778

Duran, E., Ozturk, C., & O’Sullivan, B. (2024). *Exact and Heuristic Methods for Planning and Scheduling Collaborative Manufacturing Systems*. *727 IFIP*, 53-68. Scopus. https://doi.org/10.1007/978-3-031-71743-7\_4

Dusadeerungsikul, P. O., He, X., Sreeram, M., & Nof, S. Y. (2022). Multi-agent system optimisation in factories of the future: Cyber collaborative warehouse study. *International Journal of Production Research*, *60*(20), 6072-6086. Scopus. https://doi.org/10.1080/00207543.2021.1979680

Fedorov, E., & Nechyporenko, O. (2022). *Method for Recognizing Linguistic Constructions Based on Stochastic Neural Networks*. *3171*, 104-115. Scopus. https://www.scopus.com/inward/record.uri?eid=2-s2.0-85134742070&partnerID=40&md5=50f6be4bcd90b5a2072d364a560ff7df

Fedorov, E., & Nechyporenko, O. (2023). *Linguistic Constructions Translation Method Based on Neural Networks*. *3396*, 295-306. Scopus. https://www.scopus.com/inward/record.uri?eid=2-s2.0-85160859188&partnerID=40&md5=a4423d4c000cc8c2beb371163454c59a

Fedorov, E., Nechyporenko, O., Korpan, Y., & Neskorodieva, T. (2024). *Multi-Agent Reinforcement Learning Methods with Dynamic Parameters for Logistic Tasks*. *3702*, 36-47. Scopus. https://www.scopus.com/inward/record.uri?eid=2-s2.0-85195967745&partnerID=40&md5=cc53762e8ed3df0591ebf1e62d80c46d

Fonseca-Galindo, J. C., de Castro Surita, G., Neto, J. M., de Castro, C. L., & Lemos, A. P. (2022). A multi-agent system for solving the Dynamic Capacitated Vehicle Routing Problem with stochastic customers using trajectory data mining. *Expert Systems with Applications*, *195*. Scopus. https://doi.org/10.1016/j.eswa.2022.116602

Gaida, I. W. E., Mittal, M., & Yadav, A. S. (2023). *Multi-agent-Based Ant Colony Approach for Supply Chain Delivery Routing Problem*. 135-149. Scopus. https://doi.org/10.1007/978-981-99-1328-2\_13

Gómez-Marín, C. G., Comi, A., Serna-Urán, C. A., & Zapata-Cortés, J. A. (2024). Fostering collaboration and coordination in urban delivery: A multi-agent microsimulation model. *Research in Transportation Economics*, *103*. Scopus. https://doi.org/10.1016/j.retrec.2023.101402

Gómez-Marín, C. G., Mosquera-Tobón, J. D., & Serna-Urán, C. A. (2023). Integrating Multi-agent System and Microsimulation for Dynamic Modeling of Urban Freight Transport. *Periodica Polytechnica Transportation Engineering*, *51*(4), 409-416. Scopus. https://doi.org/10.3311/PPtr.21024

Grosset, J., Fougères, A.-J., Djoko-Kouam, M., & Bonnin, J.-M. (2024). Multi-Agent simulation of autonomous industrial vehicle fleets: Towards dynamic task allocation in V2X cooperation mode. *Integrated Computer-Aided Engineering*, *31*(3), 249-266. Scopus. https://doi.org/10.3233/ICA-240735

Hamou, K. A. B., Jarir, Z., Quafafou, M., & Elfirdoussi, S. (2024). *Decision Support Systems Based on Artificial Intelligence for Supply Chain Management: A Literature Review*. *826*, 179-188. Scopus. https://doi.org/10.1007/978-3-031-47672-3\_19

Hanga, K. M., & Kovalchuk, Y. (2019). Machine learning and multi-agent systems in oil and gas industry applications: A survey. *Computer Science Review*, *34*. Scopus. https://doi.org/10.1016/j.cosrev.2019.08.002

Hasan, M., & Niyogi, R. (2020). *A meta-heuristic based multi-agent approach for last mile delivery problem*. *1*, 498-505. Scopus. https://doi.org/10.5220/0009349004980505

Hasan, M., & Niyogi, R. (2024). Deep hierarchical reinforcement learning for collaborative object transportation by heterogeneous agents. *Computers and Electrical Engineering*, *114*. Scopus. https://doi.org/10.1016/j.compeleceng.2023.109066

Herrera, M., Pérez-Hernández, M., Parlikad, A. K., & Izquierdo, J. (2020). Multi-agent systems and complex networks: Review and applications in systems engineering. *Processes*, *8*(3). Scopus. https://doi.org/10.3390/pr8030312

Huckert, J. L., Sidorenko, A., & Wagner, A. (2024). *Analysis and Assessment of Multi-Agent Systems for Production Planning and Control*. 687-698. Scopus. https://doi.org/10.1007/978-3-031-38241-3\_77

Icarte-Ahumada, G., & Riveros, E. (2023). Application of a multiagent system for resource distribution in humanitarian logistics. *Ingeniare*, *31*. Scopus. https://doi.org/10.4067/s0718-33052023000100210

Iskierka, G., Poskart, B., Krot, K., Telesiński, B., & Anthony Xavior, M. (2024). *Application of Graph Theory in Designing the Communication System of a Robotic Production Cell*. 71-78. Scopus. https://doi.org/10.1007/978-3-031-61575-7\_7

Jia, F., Zhang, S., Zheng, X.-X., & Choi, T.-M. (2023). A novel coordination mechanism to coordinate the multi-agent reverse supply chain with fairness concerns. *International Journal of Production Economics*, *265*. Scopus. https://doi.org/10.1016/j.ijpe.2023.108973

Jo, H., Lee, H., Jeon, S., Kaliappan, V. K., Anh Nguyen, T., Min, D., & Lee, J.-W. (2023). *Multi-agent Reinforcement Learning-Based UAS Control for Logistics Environments*. *913*, 963-972. Scopus. https://doi.org/10.1007/978-981-19-2635-8\_71

Kamta, H., & Sharma, S. K. (2024). Multiagent-based manufacturing: Foundations, applications, and future directions. En *The Convergence of Self-Sustaining Systems With AI and IoT* (pp. 261-279). Scopus. https://doi.org/10.4018/9798369317020.ch014

Kassa, A., Kitaw, D., Stache, U., Beshah, B., & Degefu, G. (2023). Artificial intelligence techniques for enhancing supply chain resilience: A systematic literature review, holistic framework, and future research. *Computers and Industrial Engineering*, *186*. Scopus. https://doi.org/10.1016/j.cie.2023.109714

Kessentini, M., Bellamine Ben Saoud, N., & Sboui, S. (2019). *Agent-Based Approach for Inventory Pre- and Post-disruption Decision Support*. *11775 LNAI*, 842-853. Scopus. https://doi.org/10.1007/978-3-030-29551-6\_74

Khankhour, H., Abouchabaka, J., & Rafalia, N. (2024). *An Artificial Intelligence Approach to Enhance the Optimization of the Vehicle Routing Problem*. *71 LNISO*, 114-121. Scopus. https://doi.org/10.1007/978-3-031-75329-9\_13

Khiloun, I. E., Belmabrouk, K., & Dekhici, L. (2024). Literature review on supply chains optimization using multi-agents communication and collaboration. En *Intelligent Methods and Alternative Economic Models for Sustainability* (pp. 74-94). Scopus. https://doi.org/10.4018/979-8-3693-1418-0.ch004

Khirwar, M., Gurumoorthy, K. S., Jain, A. A., & Manchenahally, S. (2023). *Cooperative Multi-agent Reinforcement Learning for Inventory Management*. *14174 LNAI*, 619-634. Scopus. https://doi.org/10.1007/978-3-031-43427-3\_37

Kim, B., Kim, J. G., & Lee, S. (2024). A multi-agent reinforcement learning model for inventory transshipments under supply chain disruption. *IISE Transactions*, *56*(7), 715-728. Scopus. https://doi.org/10.1080/24725854.2023.2217248

Köhler, P. N., Müller, M. A., Pannek, J., & Allgöwer, F. (2021). Distributed economic model predictive control for cooperative supply chain management using customer forecast information. *IFAC Journal of Systems and Control*, *15*. Scopus. https://doi.org/10.1016/j.ifacsc.2020.100125

Kusuma, P. D. (2021). Truck Scheduling Model in the Cross-docking Terminal by using Multi-agent System and Shortest Remaining Time Algorithm. *International Journal of Advanced Computer Science and Applications*, *12*(7), 134-142. Scopus. https://doi.org/10.14569/IJACSA.2021.0120715

Kusuma, P. D., & Kallista, M. (2022). COLLABORATIVE VENDOR MANAGED INVENTORY MODEL BY USING MULTI AGENT SYSTEM AND CONTINUOUS REVIEW (R, Q) REPLENISHMENT POLICY. *Journal of Applied Engineering Science*, *20*(1), 254-263. Scopus. https://doi.org/10.5937/jaes0-31532

Laouadi, M. A., Mokhati, F., & Seridi-Bouchelaghem, H. (2017). A formal framework for organization- centered multi-agent system specification: A rewriting logic based approach. *Multiagent and Grid Systems*, *13*(4), 395-419. Scopus. https://doi.org/10.3233/MGS-170277

Lehmann, J., Lober, A., Häußermann, T., Rache, A., Ollinger, L., Baumgärtel, H., & Reichwald, J. (2023). The Anatomy of the Internet of Digital Twins: A Symbiosis of Agent and Digital Twin Paradigms Enhancing Resilience (Not Only) in Manufacturing Environments. *Machines*, *11*(5). Scopus. https://doi.org/10.3390/machines11050504

Li, J., Yuan, P., Liang, L., & Cao, J. (2024). Enhancing Supply Chain Resilience in Prefabricated Buildings: The Role of Blockchain Technology in Volatile, Uncertain, Complex, and Ambiguous Environments. *Buildings*, *14*(9). Scopus. https://doi.org/10.3390/buildings14093006

Li, Y., & Wang, J. (2024). Decision-making in low-carbon supply chain networks considering demand uncertainty. *Neural Computing and Applications*, *36*(17), 9891-9901. Scopus. https://doi.org/10.1007/s00521-024-09595-0

Li, Z., Ksibi, A., & Xu, X. (2024). *Optimizing Inventory Management using a Multi-Agent LLM System*. *24*, 308-318. Scopus. https://www.scopus.com/inward/record.uri?eid=2-s2.0-85213378512&partnerID=40&md5=fa8f712c70c2d52c7775997c666eebdc

Li, Z., Xiao, L., & Xiao, Y. (2019). *Research on decision-making scheduling model of distributed multi-agent collaborative group in supply chain based on multi-agent system*. 76-80. Scopus. https://doi.org/10.1145/3328886.3328894

Liu, S., Hennequin, S., & Roy, D. (2021). *Enterprise platform of logistics services based on a multi-agents mechanism and blockchains*. *54*(1), 825-830. Scopus. https://doi.org/10.1016/j.ifacol.2021.08.097

Liu, X., Hu, M., Peng, Y., & Yang, Y. (2024). Multi-Agent Deep Reinforcement Learning for Multi-Echelon Inventory Management. *Production and Operations Management*. Scopus. https://doi.org/10.1177/10591478241305863

Liu, Y., Hadfi, R., & Ito, T. (2023). *Concession Strategy Adjustment in Automated Negotiation Problems*. *1092 SCI*, 136-143. Scopus. https://doi.org/10.1007/978-981-99-0561-4\_8

Liu, Z., Jahanshahi, H., Volos, C., Bekiros, S., He, S., Alassafi, M. O., & Ahmad, A. M. (2022). Distributed Consensus Tracking Control of Chaotic Multi-Agent Supply Chain Network: A New Fault-Tolerant, Finite-Time, and Chatter-Free Approach. *Entropy*, *24*(1). Scopus. https://doi.org/10.3390/e24010033

Liu, Z., Shirakashi, R., Kamiebisu, R., Nishi, T., & Matsuda, M. (2023). *Simulation-Based Optimization Using Virtual Supply Chain Structured by the Configuration Platform*. *56*(2), 7840-7845. Scopus. https://doi.org/10.1016/j.ifacol.2023.10.1145

Lu, M., Huang, C., & Teng, J. (2022). Multi-agent Simulation for Online Fresh Food Autonomous Delivery. *Xitong Fangzhen Xuebao / Journal of System Simulation*, *34*(6), 1185-1195. Scopus. https://doi.org/10.16182/j.issn1004731x.joss.20-1050

Ma, C., Zhang, L., You, L., & Tian, W. (2025). A Review of Supply Chain Resilience: A Network Modeling Perspective. *Applied Sciences (Switzerland)*, *15*(1). Scopus. https://doi.org/10.3390/app15010265

Maestro, J. A., Rodriguez, S., Casado, R., Prieto, J., & Corchado, J. M. (2021). *Comparison of Efficient Planning and Optimization Methods of Last Mile Delivery Resources*. *355*, 163-173. Scopus. https://doi.org/10.1007/978-3-030-68737-3\_11

Maktabifard, A., Földes, D., & Bak, B. D. (2023). *Constrained Multi-agent Path Planning Problem*. *14239 LNCS*, 450-466. Scopus. https://doi.org/10.1007/978-3-031-43612-3\_28

Matsuda, M., Nishi, T., Hasegawa, M., & Terunuma, T. (2020). *Construction of a virtual supply chain using enterprise e-catalogues*. *93*, 688-693. Scopus. https://doi.org/10.1016/j.procir.2020.04.093

Mehra, A., Saha, S., Raychoudhury, V., & Mathur, A. (2024). *DeliverAI: Reinforcement Learning Based Distributed Path-Sharing Network for Food Deliveries*. Proceedings of the International Joint Conference on Neural Networks. Scopus. https://doi.org/10.1109/IJCNN60899.2024.10651403

Mehra, A., Singh, D., Raychoudhury, V., Mathur, A., & Saha, S. (2024). Last Mile: A Novel, Hotspot-Based Distributed Path-Sharing Network for Food Deliveries. *IEEE Transactions on Intelligent Transportation Systems*, *25*(12), 20574-20587. Scopus. https://doi.org/10.1109/TITS.2024.3465217

Meziani, A., Bourouis, A., & Chebout, M. S. (2023). NeutroMAS4SCRM : a combined multi-agent system with neutrosophic data analytic hierarchy process framework for supply chain risk management. *Journal of Intelligent and Fuzzy Systems*, *44*(3), 3695-3716. Scopus. https://doi.org/10.3233/JIFS-222305

Miyajima, R., & Fujita, K. (2024). *Deep Reinforcement Learning Framework with Representation Learning for Concurrent Negotiation*. *1*, 231-239. Scopus. https://doi.org/10.5220/0012336000003636

Motsch, W., Wagner, A., & Ruskowski, M. (2024). Autonomous Agent-Based Adaptation of Energy-Optimized Production Schedules Using Extensive-Form Games. *Sustainability (Switzerland)*, *16*(9). Scopus. https://doi.org/10.3390/su16093612

Mousa, M., van de Berg, D., Kotecha, N., del Rio Chanona, E. A., & Mowbray, M. (2024). An analysis of multi-agent reinforcement learning for decentralized inventory control systems. *Computers and Chemical Engineering*, *188*. Scopus. https://doi.org/10.1016/j.compchemeng.2024.108783

Nain, P. K. S., & Kumar, A. (2022). *Supply Chain Management using Soft Computing: A Review*. 1510-1515. Scopus. https://doi.org/10.1109/ICACITE53722.2022.9823920

Ngu, E., Parada, L., Macias, J. J. E., & Angeloudis, P. (2022). Decentralised Multi-Agent Reinforcement Learning Approach for the Same-Day Delivery Problem. *Transportation Research Record*, *2676*(11), 385-395. Scopus. https://doi.org/10.1177/03611981221093324

Nguyen, A. H. T., Singh, A., Kumari, S., & Choudhary, S. (2023). Multi-agent architecture for waste minimisation in beef supply chain. *Production Planning and Control*, *34*(11), 1082-1096. Scopus. https://doi.org/10.1080/09537287.2021.1979679

Nishi, T., Debuchi, N., & Liu, Z. (2024). Distributed optimization algorithm for multi-agent optimization problems using consensus control. *Journal of Advanced Mechanical Design, Systems and Manufacturing*, *18*(5). Scopus. https://doi.org/10.1299/jamdsm.2024jamdsm0073

Nitsche, B., Brands, J., Treiblmaier, H., & Gebhardt, J. (2023). The impact of multiagent systems on autonomous production and supply chain networks: Use cases, barriers and contributions to logistics network resilience. *Supply Chain Management*, *28*(5), 894-908. Scopus. https://doi.org/10.1108/SCM-07-2022-0282

Okada, T., Sato, H., & Kubo, M. (2023). Supply Chain Network Model using Multi-Agent Reinforcement Learning for COVID-19. *International Journal of Advanced Computer Science and Applications*, *14*(2), 65-69. Scopus. https://doi.org/10.14569/IJACSA.2023.0140208

Padmavathi, S., Dharani, V. P., Maithrreye, S., Devi, M. M., & Durairaj, S. (2016). *Multi-agent framework for cloud service composition*. 1st International Conference on Emerging Trends in Engineering, Technology and Science, ICETETS 2016 - Proceedings. Scopus. https://doi.org/10.1109/ICETETS.2016.7603011

Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., Akl, E. A., Brennan, S. E., Chou, R., Glanville, J., Grimshaw, J. M., Hróbjartsson, A., Lalu, M. M., Li, T., Loder, E. W., Mayo-Wilson, E., McDonald, S., … Moher, D. (2021). The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *BMJ*, *372*, n71. https://doi.org/10.1136/bmj.n71

Patil, D., & Nezamoddini, N. (2024). *Enhancing Procurement Efficiency of Collaborative Supply Networks Using Multi-Agent Actor-Critic Algorithm*. Proceedings of the IISE Annual Conference and Expo 2024. Scopus. https://www.scopus.com/inward/record.uri?eid=2-s2.0-85206580750&partnerID=40&md5=8748229db7084f7172a4631b3699cda6

Perez, M.-J., Chargui, T., & Trentesaux, D. (2024a). A Two-Stage Optimisation Approach for a Sustainable Physical Internet Multi-Modal Barge–Road Hub Terminal. *Information (Switzerland)*, *15*(12). Scopus. https://doi.org/10.3390/info15120756

Perez, M.-J., Chargui, T., & Trentesaux, D. (2024b). *Improving the environmental impact of empty containers in water-road hubs: A physical internet approach*. *58*(19), 682-687. Scopus. https://doi.org/10.1016/j.ifacol.2024.09.221

Ponnambalam, L., Long, D. H., Sarawgi, D., Fu, X., & Mong Goh, R. S. (2015). *Multi-agent models to study the robustness and resilience of complex supply chain networks*. 7-12. Scopus. https://doi.org/10.1109/INAGENTSYS.2014.7005717

Porter, A. L., Garner, J., Carley, S. F., & Newman, N. C. (2019). Emergence scoring to identify frontier R&D topics and key players. *Technological Forecasting and Social Change*, *146*, 628-643. Scopus. https://doi.org/10.1016/j.techfore.2018.04.016

Porter, A. L., & Zhang, Y. (2012). Text clumping for technical intelligence. *Theory and Applications for Advanced Text Mining*, *10*, 50973.

Protogerou, A., Papadopoulos, S., Drosou, A., Tzovaras, D., & Refanidis, I. (2021). A graph neural network method for distributed anomaly detection in IoT. *Evolving Systems*, *12*(1), 19-36. Scopus. https://doi.org/10.1007/s12530-020-09347-0

Radisic-Aberger, O., Weisser, T., SaBmannshausen, T., Wagner, J., & Burggräf, P. (2022). *Concept of a Multi-Agent System for Optimised and Automated Engineering Change Implementation*. *2*, 1689-1698. Scopus. https://doi.org/10.1017/pds.2022.171

Raju, S., Rofin, T. M., & Pavan Kumar, S. (2023). Pricing Decisions in a Heterogeneous Dual-Channel Supply Chain Under Lead Time-Sensitive Customer Demand. En *Lecture Notes in Operations Research: Vol. Part F3787* (pp. 203-215). Scopus. https://doi.org/10.1007/978-981-19-8012-1\_14

Rebollo, M., Giret, A., Carrascosa, C., & Julian, V. (2018). *The multi-agent layer of CALMeD SURF*. *10767 LNAI*, 446-460. Scopus. https://doi.org/10.1007/978-3-030-01713-2\_31

Ren, L., Fan, X., Cui, J., Shen, Z., Lv, Y., & Xiong, G. (2022). A Multi-Agent Reinforcement Learning Method With Route Recorders for Vehicle Routing in Supply Chain Management. *IEEE Transactions on Intelligent Transportation Systems*, *23*(9), 16410-16420. Scopus. https://doi.org/10.1109/TITS.2022.3150151

Rezaei, S., & Behnamian, J. (2022). Competitive planning of partnership supply networks focusing on sustainable multi-agent transportation and virtual alliance: A matheuristic approach. *Journal of Cleaner Production*, *333*. Scopus. https://doi.org/10.1016/j.jclepro.2021.130073

Rosenberger, J., Urlaub, M., Rauterberg, F., Lutz, T., Selig, A., Bühren, M., & Schramm, D. (2022). Deep Reinforcement Learning Multi-Agent System for Resource Allocation in Industrial Internet of Things. *Sensors*, *22*(11). Scopus. https://doi.org/10.3390/s22114099

Rzevski, G., Skobelev, P., Zhilyaev, A., Lakhin, O., Mayorov, I., & Simonova, E. (2018). *Ontology-Driven Multi-Agent Engine for Real Time Adaptive Scheduling*. 14-22. Scopus. https://doi.org/10.1109/ICCAIRO.2018.00011

Saha, E., & Rathore, P. (2024). A smart inventory management system with medication demand dependencies in a hospital supply chain: A multi-agent reinforcement learning approach. *Computers and Industrial Engineering*, *191*. Scopus. https://doi.org/10.1016/j.cie.2024.110165

Sahraoui, M., & Bellaouar, A. (2024). A New Modeling Approach to Enhance Reliability, Availability, Maintainability, and Performance of Production System Equipment in a Supply Chain. *International Journal of Performability Engineering*, *20*(4), 242-252. Scopus. https://doi.org/10.23940/ijpe.24.04.p6.242252

Sahraoui, M., Bellaouar, A., & Maliki, F. (2024). A MODELING APPROACH BASED ON MULTI-AGENT SYSTEMS TO OPTIMIZE PRODUCTION CHAIN MANAGEMENT. *Academic Journal of Manufacturing Engineering*, *22*(4), 11-18. Scopus.

Sara, E., & Btissam, D. (2020). *Optimization of green reverse logistics network integrating artificial bee colony algorithm and multi-agent system: Case of medical waste*. Proceedings - 2020 5th International Conference on Logistics Operations Management, GOL 2020. Scopus. https://doi.org/10.1109/GOL49479.2020.9314763

Shaikh, S. J., Pothen, A. S., & Montreuil, B. (2023). *Hyperconnected Critical-Product Supply and Distribution System: Towards Autonomous Operations*. *56*(2), 7579-7584. Scopus. https://doi.org/10.1016/j.ifacol.2023.10.669

Sharifmousavi, M., Kayvanfar, V., & Baldacci, R. (2024). *Distributed Artificial Intelligence Application in Agri-food Supply Chains 4.0*. *232*, 211-220. Scopus. https://doi.org/10.1016/j.procs.2024.01.021

Shi, L., Guo, W., Wang, L., Bekiros, S., Alsubaie, H., Alotaibi, A., & Jahanshahi, H. (2023). Stochastic Fixed-Time Tracking Control for the Chaotic Multi-Agent-Based Supply Chain Networks with Nonlinear Communication. *Electronics (Switzerland)*, *12*(1). Scopus. https://doi.org/10.3390/electronics12010083

Shu, X., Lin, A., & Wen, X. (2024). Energy-Saving Multi-Agent Deep Reinforcement Learning Algorithm for Drone Routing Problem. *Sensors*, *24*(20). Scopus. https://doi.org/10.3390/s24206698

Singh, J., & Yadav, M. (2024). *A Cognitive Architecture Based Conversation Agent Technology for Secure Communication*. *2122 CCIS*, 1-12. Scopus. https://doi.org/10.1007/978-3-031-61298-5\_1

Singh Nain, P. K., & Kumar, A. (2023). Intelligent agent-based supply chain management using service-oriented architecture. En *Contemporary Studies of Risks in Emerging Technology, Part A* (pp. 111-126). Scopus. https://doi.org/10.1108/978-1-80455-562-020231008

Skobelev, P. (2018). *Towards autonomous ai systems for resource management: Applications in industry and lessons learned*. *10978 LNAI*, 12-25. Scopus. https://doi.org/10.1007/978-3-319-94580-4\_2

Song, G., Ifaei, P., Ha, J., Kang, D., Won, W., Liu, J. J., & Na, J. (2024). The AI circular hydrogen economist: Hydrogen supply chain design via hierarchical deep multi-agent reinforcement learning. *Chemical Engineering Journal*, *497*. Scopus. https://doi.org/10.1016/j.cej.2024.154464

Sun, B., & Sun, J. (2016). *Supply chain formation for multi-modal transport based on multi-agent*. *2016-January*, 370-375. Scopus. https://doi.org/10.1109/ICNC.2015.7378018

Sun, H., Zhang, H., & Liu, J. (2023). *Research on Inventory Control of Dual-channel Supply Chain Based on Multi-Agent*. *12645*. Scopus. https://doi.org/10.1117/12.2681116

Sun, J.-Y., Tang, J.-M., & Chen, Z.-R. (2022). Multi-agent learning mechanism design and simulation of multi-echelon supply chain. *Computers and Industrial Engineering*, *168*. Scopus. https://doi.org/10.1016/j.cie.2022.108034

Sun, T.-C., Yousefpour, A., Karaca, Y., Alassafi, M. O., Ahmad, A. M., & Li, Y.-M. (2022). DYNAMICAL INVESTIGATION AND DISTRIBUTED CONSENSUS TRACKING CONTROL OF A VARIABLE-ORDER FRACTIONAL SUPPLY CHAIN NETWORK USING A MULTI-AGENT NEURAL NETWORK-BASED CONTROL METHOD. *Fractals*, *30*(5). Scopus. https://doi.org/10.1142/S0218348X22401685

Suzuki, S., & Kraiwuttianant, O. (2024). *Quantifying the Impact of Physical Internet Systems Under Decentralized Control*. 415-421. Scopus. https://doi.org/10.1007/978-981-97-0194-0\_42

Swain, S., & Patra, M. R. (2022). *A Distributed Agent-Oriented Framework for Blockchain-Enabled Supply Chain Management*. 2022 IEEE International Conference on Blockchain and Distributed Systems Security, ICBDS 2022. Scopus. https://doi.org/10.1109/ICBDS53701.2022.9936015

Swain, S., & Patra, M. R. (2024a). A Distributed Software Agent-centric Framework for Supply Chain Networks Empowered by Blockchain: Insights into Smart Contracts. *Operations Research Forum*, *5*(2). Scopus. https://doi.org/10.1007/s43069-024-00318-8

Swain, S., & Patra, M. R. (2024b). Constructing an intelligent agent-centric framework for supply chain traceability with blockchain integration. *Frontiers of Engineering Management*. Scopus. https://doi.org/10.1007/s42524-024-3118-7

Tajima, E., Ishigaki, A., Takashima, R., Nishida, H., & Okammoto, T. (2023). Effectiveness of a Multi-Agent Cooperation Game in a Multi-Stage Supply Chain – Beer Game Experiment –. *Journal of Japan Industrial Management Association*, *73*(4 E), 234-250. Scopus. https://doi.org/10.11221/jima.73.234

Taniguchi, E., Thompson, R. G., & Qureshi, A. G. (2024). *Recent developments in urban freight analytics for collaborative city logistics*. *79*, 3-12. Scopus. https://doi.org/10.1016/j.trpro.2024.03.003

Tarhan, F. A., & Ure, N. K. (2024). Genetic-Algorithm-Aided Deep Reinforcement Learning for Multi-Agent Drone Delivery. *Drones*, *8*(3). Scopus. https://doi.org/10.3390/drones8030071

Teo, J. S.-E., Taniguchi, E., & Qureshi, A. G. (2015). Evaluation of urban distribution centers using multiagent modeling with geographic information systems. *Transportation Research Record*, *2478*, 35-47. Scopus. https://doi.org/10.3141/2478-05

Vallecillos Ruiz, F. (2024). *Agent-Driven Automatic Software Improvement*. 470-475. Scopus. https://doi.org/10.1145/3661167.3661171

Velásquez, J. (2021). *Techminer* (Versión 0.0.0) [Software]. https://github.com/jdvelasq/techminer

Velásquez, J. D. (2025). An analysis of trends, challenges, and opportunities in retail analytics. *International Journal of Market Research*, 14707853251315585.

Vijay, A., Thompson, R. G., Nassir, N., & Zhang, J. (2024). *Machine Learning Based ETA Prediction for Dock Rescheduling in Hyperconnected City Logistics Based PI-Hub Facilities*. *79*, 202-209. Scopus. https://doi.org/10.1016/j.trpro.2024.03.028

Walter, S., & Mikkola, M. (2024). Advancing networked production through decentralised technical intelligence. En *Artificial Intelligence in Manufacturing: Enabling Intelligent, Flexible and Cost-Effective Production Through AI* (pp. 281-300). Scopus. https://doi.org/10.1007/978-3-031-46452-2\_16

Wang, H., Tao, J., Peng, T., Brintrup, A., Kosasih, E. E., Lu, Y., Tang, R., & Hu, L. (2022). Dynamic inventory replenishment strategy for aerospace manufacturing supply chain: Combining reinforcement learning and multi-agent simulation. *International Journal of Production Research*, *60*(13), 4117-4136. Scopus. https://doi.org/10.1080/00207543.2021.2020927

Wang, H., Wang, S., Wang, S., & Zhou, X. (2024). *Robust Multi-vehicle Routing with Communication Enhanced Multi-agent Reinforcement Learning for Last-Mile Logistics*. *14965 LNCS*, 470-480. Scopus. https://doi.org/10.1007/978-981-97-7244-5\_41

Xu, L., Almahri, S., Mak, S., & Brintrup, A. (2024). *Multi-Agent Systems and Foundation Models Enable Autonomous Supply Chains: Opportunities and Challenges*. *58*(19), 795-800. Scopus. https://doi.org/10.1016/j.ifacol.2024.09.200

Xu, L., Mak, S., Minaricova, M., & Brintrup, A. (2024). On implementing autonomous supply chains: A multi-agent system approach. *Computers in Industry*, *161*. Scopus. https://doi.org/10.1016/j.compind.2024.104120

Xu, L., Mak, S., Proselkov, Y., & Brintrup, A. (2024). Towards autonomous supply chains: Definition, characteristics, conceptual framework, and autonomy levels. *Journal of Industrial Information Integration*, *42*. Scopus. https://doi.org/10.1016/j.jii.2024.100698

Xu, L., Proselkov, Y., Schoepf, S., Minarsch, D., Minaricova, M., & Brintrup, A. (2023). *Implementation of Autonomous Supply Chains for Digital Twinning: A Multi-Agent Approach*. *56*(2), 11076-11081. Scopus. https://doi.org/10.1016/j.ifacol.2023.10.812

Xu, W., & Dong, H. (2023). *Multi-agent System Coordination and Optimization on the Green Ecological Model and Theory of Supply Chain for Industries*. 272-282. Scopus. https://doi.org/10.1109/IIoTBDSC60298.2023.00056

Yan, M. (2015). Multi-agent collaborative mechanism and its application in E-commerce SCM. *Metallurgical and Mining Industry*, *7*(7), 70-79. Scopus.

Yang, C., Yang, R., Xu, T., & Li, Y. (2018). Negotiation model and tactics of manufacturing enterprise supply chain based on multi-agent. *Advances in Mechanical Engineering*, *10*(7). Scopus. https://doi.org/10.1177/1687814018783625

Yang, S., Ogawa, Y., Ikeuchi, K., Shibasaki, R., & Okuma, Y. (2022). Modelling the behaviour of corporations during the flood damage recovery process using multi-agent deep reinforcement learning. *Journal of Flood Risk Management*, *15*(4). Scopus. https://doi.org/10.1111/jfr3.12845

Yi, X., Lu, S., Li, D., & Liu, W. (2024). Manufacturing enterprises digital collaboration empowered by Industrial Internet Platform: A multi-agent stochastic evolutionary game. *Computers and Industrial Engineering*, *194*. Scopus. https://doi.org/10.1016/j.cie.2024.110415

Yu, C., & Wong, T. N. (2015). An agent-based negotiation model for supplier selection of multiple products with synergy effect. *Expert Systems with Applications*, *42*(1), 223-237. Scopus. https://doi.org/10.1016/j.eswa.2014.07.057

Yu, F., Zhang, C., & Yang, Y. (2022). An incentive mechanism-based negotiation model for green supply chain networks. *Transactions of the Institute of Measurement and Control*, *44*(1), 15-29. Scopus. https://doi.org/10.1177/0142331220929814

Zekhnini, K., Chaouni Benabdellah, A., & Cherrafi, A. (2024). A multi-agent based big data analytics system for viable supplier selection. *Journal of Intelligent Manufacturing*, *35*(8), 3753-3773. Scopus. https://doi.org/10.1007/s10845-023-02253-7

Zhang, B., Tan, W. J., Cai, W., & Zhang, A. N. (2023). *Multi-agent Reinforcement Learning for Improving Supply Chain Visibility in Inventory Management*. 117-118. Scopus. https://doi.org/10.1109/DS-RT58998.2023.00028

Zhang, B., Tan, W. J., Cai, W., & Zhang, A. N. (2024). Leveraging Multi-Agent Reinforcement Learning for Digital Transformation in Supply Chain Inventory Optimization. *Sustainability (Switzerland)*, *16*(22). Scopus. https://doi.org/10.3390/su16229996

Zhang, H. (2024). *Construction of a New Type of Business Management System in the Supply Chain Using Multi-agent Technology*. *1215 LNEE*, 19-27. Scopus. https://doi.org/10.1007/978-981-97-4125-0\_3

Zhang, K., Lin, X., & Li, M. (2023). Graph attention reinforcement learning with flexible matching policies for multi-depot vehicle routing problems. *Physica A: Statistical Mechanics and its Applications*, *611*. Scopus. https://doi.org/10.1016/j.physa.2023.128451

Zhang, Y., Porter, A. L., Hu, Z., Guo, Y., & Newman, N. C. (2014). «Term clumping» for technical intelligence: A case study on dye-sensitized solar cells. *Technological Forecasting and Social Change*, *85*, 26-39. Scopus. https://doi.org/10.1016/j.techfore.2013.12.019

Zhao, D., & Wang, X. (2024). EVOLUTIONARY GAME OF DIGITAL DECISION-MAKING IN SUPPLY CHAINS BASED ON SYSTEM DYNAMICS. *RAIRO - Operations Research*, *58*(1), 475-510. Scopus. https://doi.org/10.1051/ro/2023190

Zheng, X.-X., Li, R., Jia, F., Liu, Z.-Y., & Yang, Y. (2024). Coopetition strategies in a two-stage, multi-agent supply chain under hybrid carbon trading mechanisms. *International Journal of Production Research*. Scopus. https://doi.org/10.1080/00207543.2024.2392635

Zhu, T., Fernandez, G. I., Togashi, C., Liu, Y., & Hong, D. (2022). *Feasibility Study of LIMMS, A Multi-Agent Modular Robotic Delivery System with Various Locomotion and Manipulation Modes*. 30-37. Scopus. https://doi.org/10.1109/UR55393.2022.9826272

Zhu, Y., Zhan, Y., Huang, X., Chen, Y., Chen, Y., Wei, J., Feng, W., Zhou, Y., Hu, H., & Ye, J. (2023). *OFCOURSE: A Multi-Agent Reinforcement Learning Environment for Order Fulfillment*. *36*. Scopus. https://www.scopus.com/inward/record.uri?eid=2-s2.0-85191145734&partnerID=40&md5=26667f5a8699acd5383176e477368c23