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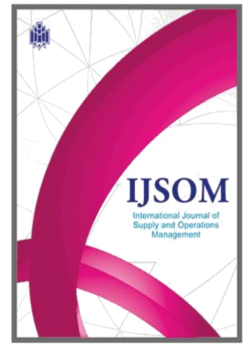

Operations Research and Artificial Intelligence for Supply Chain Planning: A Systematic Literature Review

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Abstract

This systematic review analyzes 55 peer-reviewed scientific articles published between 2020 and 2024, examining the application of Artificial Intelligence (AI) in supply chain optimization and planning. The study focuses on AI methodologies, their implementation across various industrial sectors, and their impact on enhancing operational efficiency, reducing logistics costs, and improving adaptability to market dynamics. It highlights how AI-driven approaches are transforming traditional supply chain management practices through real-time decision-making, predictive analytics, and automation. The review identifies key advancements in AI technologies, such as machine learning, deep learning, and reinforcement learning, along with their applications in demand forecasting, inventory management, and transportation planning. Additionally, it explores critical challenges and barriers to adoption, including data quality issues, technological integration complexities, and organizational readiness, while emphasizing existing research gaps. To address these gaps, the study proposes a novel AI-based framework, providing actionable insights for researchers, industry professionals, and policymakers aiming to drive innovation and resilience in supply chain management.

Keywords: Artificial Intelligence; Supply chain; Planning; Operations Research; Logistics.

1. Introduction

The global supply chain industry is undergoing profound transformation, driven by rising operational costs, heightened risk exposure, and rapidly evolving market demands. In this increasingly complex and volatile environment, businesses are turning to advanced technologies to maintain agility, responsiveness, and competitiveness. Among these technologies, Artificial Intelligence (AI) has emerged as a transformative enabler, offering advanced capabilities in machine learning, optimization algorithms, and real-time analytics. These tools enhance supply chain performance by improving demand forecasting, inventory control, transportation planning, and procurement decision-making.

In recent years, the application of AI in Supply Chain Management (SCM) has expanded significantly driven in part by disruptions such as the COVID-19 pandemic, which revealed critical weaknesses in traditional supply chain models. AI is no longer limited to predictive analytics but now supports supplier selection, sustainability analysis,

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and even autonomous decision systems. However, despite this momentum, academic literature remains fragmented. Many existing reviews lack methodological transparency, focus on a narrow time window, or fail to provide decision- level classifications and practical implications.
Recent studies highlight AI's growing role in supply chain management. Mahraz, Benabbou, and Berrado, 2022 show that machine learning improves demand forecasting, inventory optimization, and transport planning, though real-time decision integration remains limited. Muhammad Usman Tariq, 2023 demonstrates that AI enhances resilience and flexibility during high uncertainty, supporting automation, risk detection, adaptive logistics, and sustainability. Together, these studies emphasize AI as a key driver of efficiency, resilience, and sustainability in modern supply chains.

Moreover, despite the existence of several literature reviews on AI in supply chain management, none provides a comprehensive classification and detailed case-by-case analysis of the selected articles. This gap limits the ability to fully understand the nuances of AI applications across different decision-making levels and industrial sectors. Our study addresses this shortcoming by offering a systematic and granular classification framework that examines each article in detail, enabling a richer synthesis of methodological approaches, thematic focuses, and practical implications.

Several prior literature reviews have addressed the intersection of AI and SCM. For example, Addo-Tenkorang & Helo, 2016 explored early applications of big data and AI in logistics; Dubey et al., 2020 developed a conceptual framework linking AI to dynamic capabilities; and Zhang and Ha, 2020 reviewed machine learning applications for demand forecasting. While valuable, these studies focus predominantly on pre-2020 literature and generally include fewer than 40 articles. They also lack bibliometric analyses, sector-specific mappings, and comprehensive decision-level classifications.

Several previous reviews on AI in supply chain management exhibit notable limitations in scope, timeframe, and corpus size. Addo-Tenkorang & Helo, 2016 focused on early applications of big data and AI up to 2016, thus missing recent advances related to resilience and sustainability. Dubey et al, 2020 analyzed fewer than 40 publications mostly before 2020 and did not provide in-depth bibliometric or sectoral analyses. Zhang and Ha, 2020 concentrated on machine learning for demand forecasting, limiting their scope both functionally and temporally. In contrast, this systematic review covers 55 peer-reviewed articles from 2020 to 2024, incorporates rigorous bibliometric methods, offers a detailed decision-level classification, and maps performance dimensions such as efficiency, resilience, and sustainability. This comprehensive approach delivers an updated and operational perspective on AI's role in modern supply chains.

In light of these gaps, this paper presents a systematic literature review of 55 peer-reviewed scientific articles published between 2020 and 2024, aiming to provide a comprehensive and up-to-date assessment of how AI and OR contribute to supply chain planning and optimization across various industries. The primary objective of this study is to examine the intersection between AI-driven technologies and supply chain planning, with a particular focus on how these technologies support decision-making at the strategic, tactical, and operational levels. The specific objectives are to:

- Identify and analyze key co-occurrence networks and methodological clusters in the current literature.
- Map the emerging thematic axes related to AI and OR in SCM;
- Highlight the most influential authors, institutions, and journals in the field;
- And synthesize findings around the core performance dimensions of modern supply chains: efficiency (cost and speed), resilience (adaptability to disruption), and sustainability (economic, social, and environmental).

Ultimately, this study extends existing scholarships by presenting a nuanced and holistic perspective on AI's transformative potential in SCM. It offers clear strategies to address the challenges that hinder AI deployment, such as data quality, technological integration, and organizational readiness and highlights persistent research gaps. To bridge these gaps, the study proposes a novel AI-based framework and delivers actionable insights for researchers and practitioners seeking to foster innovation, agility, and long-term resilience in supply chain systems. The remainder of this paper is structured as follows: Section 2 outlines the methodology and selection criteria used for the literature review. Section 3 presents the classification framework and key trends identified in the selected studies. Section 4 discusses the findings in relation to performance dimensions and implementation challenges. Finally, Section 5 concludes with recommendations for future research and practical applications.

Table 1. Comparative Overview of Major Literature Reviews on AI in Supply Chain Management

Criterion	Addo-Tenkorang & Helo (2016)	Dubey et al. (2020)	Zhang & Ha (2020)	Our Systematic Review (2020-2024)
Time Period Covered	Up to 2016	Mainly before 2020	Up to 2020	2020 to 2024
Number of Articles Analyzed	Fewer than 40	Fewer than 40	Fewer than 40	55
Thematic Scope	Big data and AI in logistics (early applications)	AI linked to dynamic capabilities in SCM	Machine learning for demand forecasting	Broad, covering various AI domains in SCM
Methodological Approach	Traditional review, no bibliometrics	Conceptual framework, no detailed bibliometrics	Sector-specific limited review	Systematic review with detailed bibliometric analysis
Detailed Classification / Analysis	Absent	Absent	Absent	In-depth decision-level classification and case-by-case analysis
Industrial Sectors Covered	General, no sector mapping	General, no sector mapping	Specific sector (demand forecasting)	Sectoral and thematic mapping
Practical Implications	Limited	Conceptual framework, few practical applications	Limited	Synthesis of practical implications and operational strategies
Recency / Inclusion of Recent Disruptions	Not considered (pre-COVID-19)	Partially (up to 2020)	Pre-COVID-19	Includes recent impacts, notably COVID-19

2. Materials & Methods

This study adopts a methodological framework based on the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) protocol. PRISMA ensures that all phases of the research are conducted systematically and transparently, providing a structured approach to summarizing findings. This standardized process facilitates the identification, evaluation, and synthesis of relevant studies in a reproducible manner, enabling others to assess the overall quality of the review.

Figure 1. Process PRISMA

The research is based on a comprehensive review of the literature on the optimization and integration of artificial intelligence (AI) in supply chains. Articles were sourced from three major scientific databases: Web of Science, ScienceDirect, and Google Scholar.

2.1. Pilot Research and Research Question

In the initial phase, a pilot study was conducted to gain a deeper understanding of the field and existing literature. This phase involved identifying relevant sources using predefined search strings in selected electronic databases (see Table 1). The pilot study played a crucial role in defining the inclusion and exclusion criteria for selecting literature. Articles were chosen based on their titles, abstracts, and keywords, with a focus on research areas such as engineering, computer science, operations research and management, robotics, and other technological domains.

Table 2. Research protocol for selected literary sources

Databases	*Parts of the article searched*	*Research Areas*	*Research chain*	*Duration*
Web of Science, Science direct Scopus, IEEE Xplore and Springer	*Title, Keywords, abstract*	*Engineering, Computer Science, Operations Research, Management Science, Robotics, Science Technology, Other Topics…*	*« Artificial intelligence» AND « Keywords », «Optimization »AND « Keywords », « Supply chain » AND « Keywords »*	*2020, 2021, 2022, 2023, 2024*

The keywords used were categorized into three main groups:

- Category A: Artificial Intelligence (e.g., machine learning, deep learning, neural networks).
- Category B: Supply Chain (e.g., upstream, procurement).
- Category C: Optimization (e.g., algorithmic, optimization, operations research).

This structured approach allowed us to pinpoint the core themes to be explored in the study.

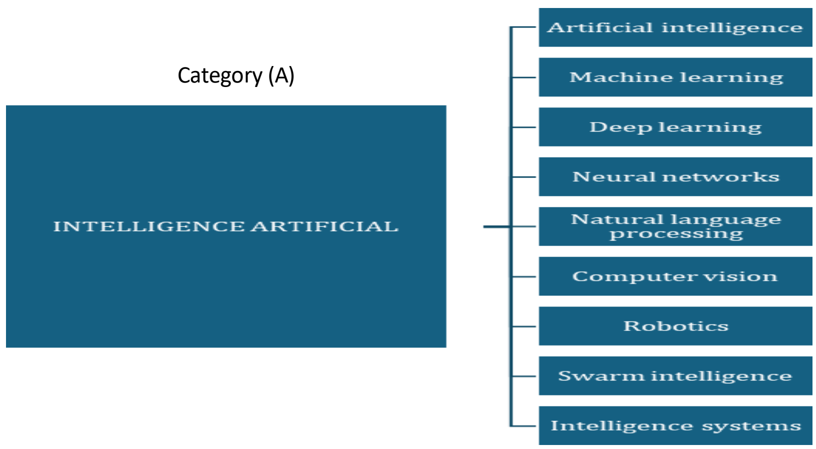

Figure 2. Keywords related to artificial intelligence used

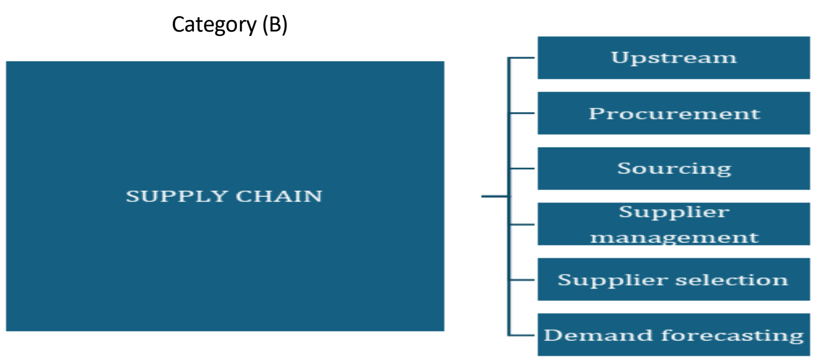

Figure 3. Keywords related to supply chain that used

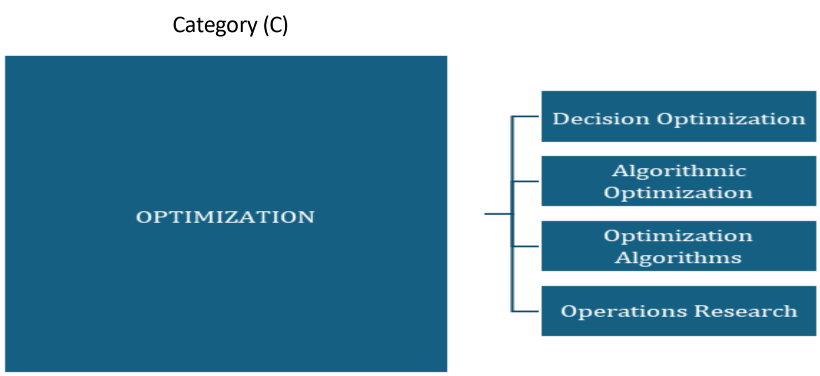

Figure 4. Keywords terms associated with optimization use

2.1.1. Research Question

To ensure the effectiveness and coherence of this systematic review, a set of well-defined research questions was established during the initial pilot study phase. These questions served as the foundation for the review's scope, guiding both the literature search strategy and the analytical framework used to synthesize the findings. Each question was carefully formulated to capture a specific dimension of the intersection between Artificial Intelligence (AI) and supply chain planning, ensuring a comprehensive and structured exploration of the topic.
The three research questions underpinning this review are as follows:

Q1: What are the main artificial intelligence techniques used in supply chain optimization and planning?

Artificial Intelligence (AI) optimizes the supply chain through several powerful techniques. Machine learning is used for demand forecasting, inventory management, and anomaly detection, while deep learning enables complex forecasting and the analysis of images or text. Reinforcement learning learns how to make real-time decisions, useful for robotics or delivery optimization. Optimization algorithms, such as genetic algorithms or simulated annealing, are applied to plan routes or production schedules. Natural Language Processing (NLP) automates contract reading or supplier communication. Computer vision is used for quality inspection or inventory monitoring via cameras and drones. Finally, multi-agent systems help coordinate between various actors in the supply chain. Together, these techniques enable a more agile, predictive, and autonomous supply chain.

Q2: How does the implementation of artificial intelligence optimize supply chain planning and management, and what are the impacts of these technologies on operational efficiency and strategic decision-making?

The implementation of Artificial Intelligence (AI) in supply chain planning and management significantly enhances both operational efficiency and strategic decision-making by enabling accurate demand forecasting, dynamic inventory optimization, and intelligent route planning. AI techniques like machine learning and deep learning analyze vast historical and real-time data to predict trends, reduce stockouts, and optimize production schedules. Natural Language Processing automates procurement and improves supplier analysis, while reinforcement learning supports real-time logistics decisions. Additionally, AI-powered systems improve risk detection and response, enabling faster adaptation to disruptions. These technologies not only streamline day-to-day operations but also empower leaders with predictive insights, leading to more informed, agile, and resilient supply chain strategies.

Q3: What are the challenges and barriers to the adoption of artificial intelligence in supply chain optimization and planning, and what solutions are proposed in the literature to overcome these obstacles?

The adoption of Artificial Intelligence (AI) in supply chain optimization and planning encounters several intertwined challenges that can slow or block its integration. A major barrier is the lack of high-quality, standardized, and accessible data, as many companies deal with siloed information across departments or partners, which affects the performance of AI models. Additionally, integration with legacy systems remains complex, since older enterprise resource planning (ERP) or logistics systems often lack the interfaces or flexibility needed to adopt advanced AI technologies. High implementation costs, including investments in infrastructure, software, and skilled personnel, pose another hurdle especially for small and medium-sized enterprises. Furthermore, there's a shortage of professionals who possess both supply chain and AI expertise, making it difficult to design and maintain effective solutions.

Organizational factors also play a role: resistance to change, fear of job displacement, and a lack of trust in AI-driven decisions can delay or derail projects. Lastly, ethical and security concerns such as data privacy, algorithmic bias, and vulnerability to cyberattacks raise serious questions. To address these issues, the literature recommends several strategies: improving data governance and interoperability, promoting gradual and modular integration through cloud-based or API- enabled AI tools, upskilling employees through training programs, fostering a collaborative culture that involves stakeholders early, and conducting pilot projects that provide measurable results to build trust and justify investment. These approaches collectively aim to reduce barriers and create the conditions necessary for a successful and sustainable AI- driven supply chain transformation

Localization of Studies

To locate relevant studies, we selected appropriate search engines and well-defined search strings. To ensure broad access to a diverse range of pertinent documents over a specified time frame, we relied on three widely recognized databases for peer-reviewed literature: ScienceDirect, Web of Science, and Google Scholar.
The search strings were designed to cover three distinct thematic areas:

- **Artificial Intelligence**: including terms such as “artificial intelligence”, “machine learning”, “deep learning”, “neural networks”, “natural language processing”, “computer vision”, “robotics”, “swarm intelligence”, “intelligence systems”.
- **Supply Chain:** covering keywords such as “upstream”, “procurement”, “sourcing”, “supplier management”, “supplier selection”, “demand forecasting”
- **Optimization:** including terms such as: “decision optimization”, “algorithmic optimization”, “optimization algorithms”, “operations research”.

Each search string was carefully crafted to maximize the relevance of the retrieved results and ensure alignment with the research objectives.

2.2. Selection and Evaluation of Studies

To ensure the rigor and relevance of the systematic review, a set of well-defined inclusion and exclusion criteria was applied during the article selection process. These criteria helped filter out irrelevant, outdated, or non-peer-reviewed studies, thereby ensuring the quality and coherence of the final dataset. The selection focused on articles that specifically addressed the application of Artificial Intelligence (AI) and Operations Research (OR) techniques in supply chain planning and optimization, within the targeted time frame from 2020 to 2024. Table 2 summarizes the key inclusion and exclusion parameters used in this review.
Table 3 outlines the methodological inclusion and exclusion criteria used to select articles for this research. Publications must originate from recognized databases (e.g., Web of Science, Scopus, IEEE Xplore) and must have been published between 2020 and 2024. The selected articles should focus on the application of artificial intelligence in supply chain optimization and include empirical data or case studies. Articles written in languages other than English, published before 2020, or lacking relevance to the topic are excluded. This selection process ensures the reliability of the data and its alignment with the study's objectives.

Table 3. Inclusion and exclusion Criteria

Inclusion	Exclusion
Articles sourced from databases: Web of Science, ScienceDirect, Scopus, IEEE Xplore, Springer	Articles not written in English
Analysis of titles, abstracts, and keywords to ensure relevance	Studies that do not specifically address supply chain optimization or planning
Publications in relevant categories (e.g., engineering, computer science)	Non-peer-reviewed publications, such as opinion pieces or editorials
Articles published in peer-reviewed journals	Articles published prior to 2020
Studies focusing on the application of artificial intelligence in supply chain optimization and planning	
Studies providing empirical data or case studies	
Publications between 2020 and 2024	

Table 4. Research Results

Keywords	Deep Learning	IA	Machine Learning	Natural Language Processing	Computer Vision	Operations Research	Automation	Genetic algorithms	Total
Optimization and Upstream	50 (3)	50 (3)	45 (5)	22 (0)	1 (1)	10 (2)	-	-	**187 (13)**
Supplier management	1 (1)	3 (3)	2 (1)	-	-	-	17 (3)	2 (1)	**25 (9)**
Sourcing	45 (1)	24 (2)	72 (1)	34 (1)	22 (1)	6 (1)	25 (3)	3 (1)	**231 (11)**
Procurement	87 (19)	1 (1)	-	13 (2)	4 (0)	3 (1)	47 (3)	_	**155 (25)**
Total	**183 (24)**	**78 (9)**	**119 (7)**	**69 (3)**	**27 (2)**	**19 (4)**	**89 (9)**	**5 (2)**	**598 (55)**

The selection process of articles was conducted based on predefined criteria to ensure relevance and quality. This rigorous process reduced the pool of articles from an initial count of 598 to 55 articles for detailed analysis and synthesis. As illustrated in Table 4, the numbers without parentheses represent the articles retained after the initial database search and the application of the first set of inclusion/exclusion criteria. In contrast, the numbers in parentheses indicate the articles selected following the application of a second set of criteria, which specifically aligned with the research objectives of this study.

2.3. Analysis and Synthesis

The analysis and synthesis phase represents a critical component of this systematic review, aiming to transform the collected body of literature into meaningful insights that respond to the established research questions. This phase involves both quantitative and qualitative techniques to identify patterns, classify thematic trends, and extract conceptual frameworks related to the use of Artificial Intelligence (AI) and Operations Research (OR) in supply chain planning. To conduct a thorough analysis, the 55 selected articles were examined in detail, focusing on key characteristics relevant to the research questions. These characteristics included:

- Study domains such as supply chain management, optimization, planning, and logistics.
- Specific subdomains explored within the studies.
- AI technologies and techniques employed.
- Results and findings presented.
- Industries targeted for improvement.

First, a descriptive analysis was conducted to map the distribution of the selected articles over time, by geographical region, industry sector, and type of publication. This bibliometric profiling provided a foundational understanding of how academic interest in AI for supply chain planning has evolved between 2020 and 2024.
Second, a content-based synthesis was applied to classify the reviewed articles according to the type of AI technique used (e.g., machine learning, deep learning, metaheuristics, reinforcement learning), the nature of the supply chain function addressed (e.g., demand forecasting, inventory optimization, transportation planning), and the decision level (strategic, tactical, operational) at which these technologies are deployed. The synthesis also involved identifying methodological clusters and co-occurrence networks based on keyword analysis, allowing for the emergence of thematic groupings within literature. These clusters help to reveal prevailing research trends and underexplored areas. In addition, real-world case applications, when present, were isolated and examined to assess the extent to which theoretical approaches have been translated into practical implementations. To further enrich the synthesis, we evaluated the impacts and benefits reported in the studies in terms of operational efficiency, cost reduction, supply chain agility, and decision-making support. Conversely, the review also highlighted challenges and limitations frequently mentioned by authors, such as data availability, model complexity, interpretability, and organizational resistance.

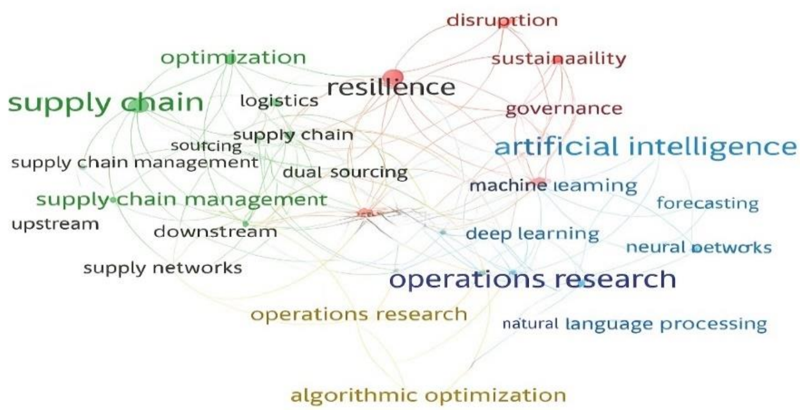

Figure 5. Keyword co-occurrence map (2020–2024) generated by VOS view

Overall, this analytical phase served to consolidate the fragmented body of knowledge into a structured and comprehensive overview. The results are presented in tabular and graphical forms in the next sections, offering a holistic view of how AI and OR are currently shaping supply chain planning, and laying the groundwork for both theoretical advancement and managerial application. More than that, the synthesis aimed to identify and establish connections between these characteristics, providing a comprehensive understanding of AI's role in supply chain optimization and planning. This process enabled the recognition of recurring patterns, research gaps, and novel contributions within literature.

2.4. Bibliometric Mapping and Keyword Co-occurrence Analysis

To further enhance the synthesis, a bibliometric mapping of keyword co-occurrence was conducted using VOSviewer. The analysis of the 55 selected articles revealed five major thematic clusters, each representing a specific focus in the application of Artificial Intelligence (AI) and Operations Research (OR) to supply chain management. The figure below illustrates the keyword co-occurrence network, where node size represents frequency, and colors indicate thematic clusters.

Table 5. Thematic Clusters from the Keyword Co-occurrence Map in Supply Chain Research

Cluster / Theme	Associated Keywords	Observations
□**Supply Chain & Logistics**	supply chain, supply chain management, logistics, sourcing, dual sourcing, supply networks, upstream, downstream	Structural and operational aspects of supply chain management
● **Artificial Intelligence**	artificial intelligence, machine learning, deep learning, neural networks, natural language processing, forecasting	AI technologies used for analysis, prediction, and automation in the supply chain
□ **Operations Research**	operations research, algorithmic optimization, optimization	Quantitative methods for decision support and modeling
●**Resilience & Sustainability**	resilience, disruption, sustainability, governance	Strategic concerns related to disruptions, sustainability, and governance

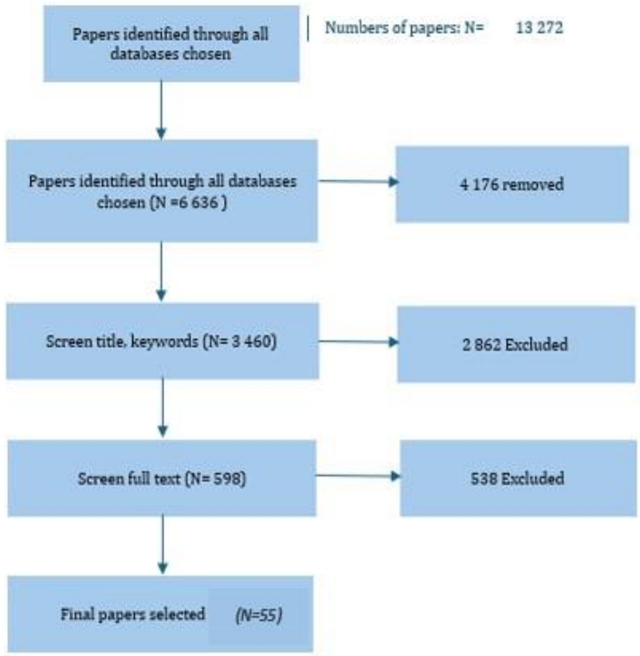

Figure 6. Articles selection process (using PRISMA)

The keyword co-occurrence map highlights the main research directions in supply chain planning, centered around artificial intelligence (AI) and operations research (OR). It reveals several thematic clusters: the logistics environment (supply chain, sourcing), AI technologies (machine learning, deep learning), OR methods (optimization), and cross-cutting issues such as resilience, sustainability, and governance. The use of the PRISMA method reflects the rigor of the systematic review. Overall, the map confirms the relevance of a hybrid AI/OR approach and emphasizes current research trends in this field.

3. Results

The systematic literature review commenced by inputting keywords into the selected databases, yielding an initial set of 13,272 articles. The first inclusion criterion, which limited the publication period to 2020–2024, reduced this number to 6,636 articles. Subsequently, the application of a research domain filter refined the selection to studies within the fields of Engineering, Computer Science, Operations Research & Management Science, Robotics, and Science & Technology (Other Topics), narrowing the count to 3,460 articles. The final preselection phase focused on assessing the alignment of article abstracts with the research theme, further reducing the pool to 598 articles. After a detailed review of these abstracts, 55 articles were ultimately deemed highly relevant to the research questions and included in this systematic literature review.

3.1. Statistics of Articles

Out of the 55 articles identified for review, 13 were published in 2022, 14 in 2023, 09 in 2021, 10 in 2020 and in 2024. The statistical analysis of the selected articles provides valuable insights into the evolution, distribution, and scope of academic research at the intersection of Artificial Intelligence and supply chain planning. By examining variables such as the year of publication, geographic origin of contributions, journal sources, and institutional affiliations, this section highlights not only the growing scholarly interest in the topic but also the regional and disciplinary diversity of the field. By establishing this quantitative foundation, the statistical overview contributes to the bibliometric rigor of the review and sets the stage for a more detailed qualitative synthesis of methods, decision levels, and thematic focuses presented in subsequent sections.

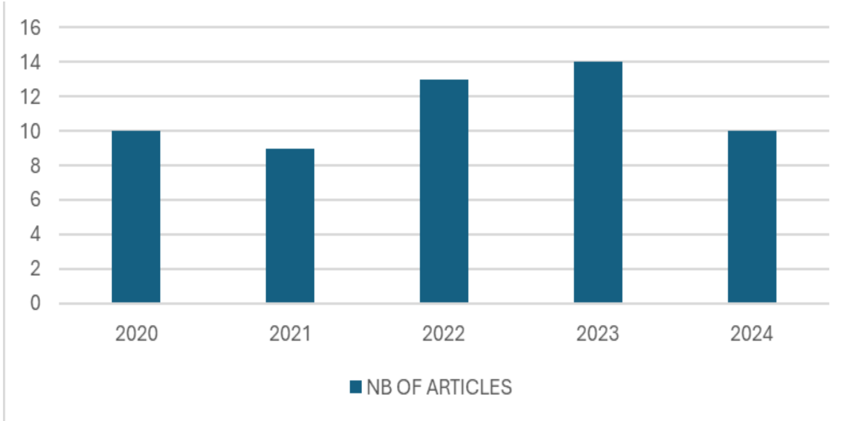

Figure 7. Number of articles per year

3.2. Categorical Analysis of Literature

The categorical analysis represents a core component of this systematic review, enabling a structured classification of the selected articles based on multiple analytical dimensions. Unlike purely descriptive overviews, this analysis goes beyond publication metadata to examine how AI and OR techniques are applied across specific supply chain functions and decision-making levels. By organizing the literature according to categories such as the type of AI method, targeted supply chain domain (e.g., demand forecasting, inventory management, logistics), and management level (strategic, tactical, operational), this approach facilitates a deeper understanding of the technological landscape and its managerial relevance. This categorization not only helps to reveal dominant research patterns but also highlights underrepresented areas where further investigation is needed. For instance, while some techniques such as machine learning are widely applied across multiple domains, others (e.g., reinforcement learning or hybrid OR-AI models) remain underexplored in real-world settings. Additionally, this section identifies which decision levels are most frequently addressed in the literature, providing valuable insights for both scholars and practitioners seeking to align AI solutions with hierarchical planning needs. By combining methodological precision with managerial relevance, the categorical analysis bridges the gap between technical innovation and strategic application, offering a multidimensional view of how AI and OR are currently shaping the future of supply chain planning.

They cover topics such as rapid production forecasting for heterogeneous gas-condensate reservoirs, the potential applications of ChatGPT, and carbon footprint management using AI algorithms. The studies also examine pharmaceutical supply chain optimization, wind farm operations prediction, and inventory control in dual-sourcing systems utilizing recurrent neural networks. Additionally, hierarchical reinforcement learning is investigated for crude oil supply chain planning, while deep learning methods are applied to generate energy supplier profiles. Innovative approaches include robotic process automation for document management, blockchain for traceability and advance payments, and combinatorial optimization. The articles further discuss large-scale AI adoption across various sectors, technological disruptions in retail, and supplier rationalization. Overall, these studies highlight a significant digital transformation in the field, with technological solutions designed to enhance efficiency, transparency, and sustainability in modern supply chains (See Tables 5 and 11).

Table 6 presents the following 55 articles:

- **A1 :** Rapid Production Forecasting for Heterogeneous Gas-Condensate Shale Reservoir
- **A2 :** ChatGPT in Supply Chains: Exploring Potential Applications, Benefits and Challenges
- **A3 :** Carbon Footprint Management in Global Supply Chains: A Data-Driven Approach Utilizing Artificial Intelligence Algorithms
- **A4 :** Integrating Artificial Intelligence and Data Analytics for Supply Chain Optimization in the Pharmaceutical Industry
- **A5 :** A Bibliometric Analysis of the Application of Machine Learning
- **A6 :** Control of Dual-Sourcing Inventory Systems Using Recurrent Neural Networks
- **A7 :** Hierarchical Reinforcement Learning for Crude Oil Supply Chain Scheduling
- **A8 :** Review of Application of Artificial Intelligence Techniques in Petroleum Operations
- **A9 :** Real-Time Large-Scale Supplier Order Assignments Across Two-Tiers of a Supply Chain with Penalty and Dual-Sourcing
- **A10 :** Generation Method of Power Supplier Portrait Based on Deep Learning BCCM and Multi-Aspect
- **A11 :** Building Resilience and Innovation Through Intelligent Diversity
- **A12 :** New AI Techniques for Combinatorial Optimization
- **A13 :** A Hybrid Bi-Objective Optimization Approach for Joint Determination of Safety Stock and Safety Time Buffers in Multi-Item Single-Stage Industrial Supply Chains
- **A14 :** The Single-Sourcing Versus Multisourcing Decision in Information Technology Outsourcing
- **A15 :** Towards Artificial Intelligence at Scale in the Chemical Industry
- **A16 :** Conceptual Framework for Efficient Inbound Supply Chain Analytics
- **A17 :** Technological Disruption in Grocery Retail: An Overview of the Last Decade
- **A18 :** Model Complexity of Deep Learning: A Survey
- **A19 :** The Potential of Machine Learning for a More Responsible Sourcing of Critical Raw Materials
- **A20 :** Digital Twin Framework for Machine Learning-Enabled Integrated Production and Logistics Processes
- **A21 :** Forecasting Very Short-Term Wind Power Generation Using Deep Learning, Optimization and Data Decomposition Techniques
- **A22 :** Well Control Space Out: A Deep-Learning Approach for the Optimization of Drilling Safety Operations
- **A23 :** A Comparison of Optimization Algorithms for Deep Learning
- **A24 :** Verizon Uses Advanced Analytics to Rationalize Its Tail-Spend Suppliers
- **A25 :** Injection of Knowledge in a Sourcing Recommender System
- **A26 :** Internet of Behaviors: Conceptual Model, Practical and Theoretical Implications for Supply Chain and Operations Management
- **A27 :** A Machine Learning-Based Sample Average Approximation for Supplier Selection with Option Contract in Humanitarian Relief
- **A28 :** Developing a Smart Green Supplier Risk Assessment System Integrating Natural Language Processing and Life Cycle Assessment Based on AHP Framework: An Empirical Study
- **A29 :** Intermittent Demand Forecasting for Spare Parts with Little Historical Information
- **A30 :** Predicting Construction Project Compliance with Machine Learning Model: Case Study Using Portuguese Procurement Data
- **A31 :** The Poverty of Ethical AI: Impact Sourcing and AI Supply Chains
- **A32 :** Global Database of Cement Production Assets and Upstream Suppliers
- **A33 :** Efficient Emission Reduction Through Dynamic Supply Mode Selection
- **A34 :** Automated Natural Language Processing-Based Supplier Discovery for Financial Services
- **A35 :** Intelligent Robotic Process Automation for Supplier Document Management on E-Platforms
- **A36 :** Procurement Volume Prediction of Cross-Border E-Commerce Platform Based on BP-NN
- **A37 :** Purchase Decision of GPPS: An Empirical Study Based on Machine Learning in China

- **A38 :** Procurement, Traceability and Advance Cash Credit Payment Transactions in Supply Chain Using Blockchain Smart Contracts
- **A39 :** Data Quality Barriers for Transparency in Public Procurement
- **A40 :** Challenges in Developing and Deploying AI in the Engineering, Procurement and Construction Industry
- **A41 :** Prescriptive Analytics for Commodity Procurement Applications
- **A42 :** Award Price Estimator for Public Procurement Auctions Using Machine Learning Algorithms: Case Study with Tenders from Spain
- **A43 :** Data Mining to Identify Anomalies in Public Procurement Rating Parameters
- **A44 :** A Machine Learning Approach for Predicting Hidden Links in Supply Chain with Graph Neural Networks
- **A45 :** A Hybrid Machine Learning Method for Procurement Risk Assessment of Non-Ferrous Metals for Manufacturing Firms
- **A46 :** Industry 4.0 Technology Provision: The Moderating Role of Supply Chain Partners to Support Technology Providers
- **A47 :** Towards Cost-Optimal Energy Procurement for Cooling as a Service: A Data-Driven Approach
- **A48 :** Forecasting Demand Profiles of New Products
- **A49 :** Data-Driven Optimization for Commodity Procurement Under Price Uncertainty
- **A50 :** Artificial Intelligence in Purchasing: Facilitating Mechanism Design-Based Negotiations
- **A51 :** An Analytics Architecture for Procurement
- **A52 :** Modeling the Enablers of Supply Chain Strategies and Information Technology: Improving Performance Through TISM Approach
- **A53 :** Contracting in Brazilian Public Administration: A Machine Learning Approach
- **A54 :** Autonomous Procurement System (APS): Pro Forma Development
- **A55 :** A Journey to the Future Workplace: Marketing Technology Sourcing

Table 6. Analysis of Literature

Title	Solutions (RO and IA)	Methods (RO and IA)	SupplyChain Focus	Years	Country and University	Decision Level
A1	AI-based reservoir forecasting (IA)	Machine learning/time-series forecasting (IA)	Upstream Oil & Gas SC	2024	États-Unis,Texas A&M University	Tactical
A2	Generative AI for SCM communication & decision support (IA)	NLP-based large language models (IA	Cross-Industry SCM	2024	Poland University of Economics and Business in Pozna	Strategic
A3	AI-driven carbon footprint reduction strategies (IA)	Data-driven optimization & ML (RO & IA)	Sustainability in Global SC	2024	China, Harbin Institute of Technology	Strategic
A4	AI and analytics solutions (IA)	ML optimization (RO & IA)	Pharmaceutical SC	2024	India, University of Delhi.	Tactical
A5	Overview of ML applications (IA)	Bibliometric analysis (IA)	Upstream & midstream Oil & Gas SC	2023	Iran, University of Tehran	Strategic

Table 6 (continued). Analysis of Literature

Title	Solutions (RO and IA)	Methods (RO and IA)	SupplyChain Focus	Years	Country and University	Decision Level
A6	AI-based inventory control (IA)	RNNs (IA)	Inventory management in SC	2023	German, University of Mannheim	Operational
A7	AI-based scheduling (IA)	Hierarchical RL (IA)	Crude oil SC scheduling	2023	China, University of Science	Operational
A8	AI applications in petroleum (IA)	Literature review (IA)	Petroleum SC	2023	Iran, Shahid Beheshti University	Strategic
A9	Real-time optimization (RO) + AI (if ML used)	Possibly mixed-integer programming + ML (RO & IA)	Supplier order allocation	2023	United Kingdom, University	Operational
A10	Deep learning solutions	Deep learning	Power supplier management	2023	China, Xi'an Jiaotong University	Tactical
A11	Intelligent supplier engagement	Possibly ML or analytics-based approach	Supplier management in SC	2022	United Kingdom, University	Strategic
A12	Combinatorial optimization (RO & IA)	Novel AI optimization techniques	Cross-Industry SCM	2022	Singapore, Nanyang Technological University	Tactical
A13	Hybrid optimization approach (RO)	Bi objective optimization (RO)	Inventory & lead time mgmt in SCM	2022	Portugal, University of Porto	Tactical
A14	Decision-making models (RO)	Possibly game theory or MIP for sourcing (RO)	IT outsourcing SC	2023	USA – University of South Carolina	Strategic
A15	Large-scale AI implementation (IA)	Various AI/ML tools (IA)	Chemical SC	2022	USA - University of Notre Dame	Strategic
A16	Analytics-driven inbound SC solutions (IA)	Conceptual framework (IA/RO not specified)	Inbound logistics SC	2022	Indonesia Bandung Institute of Technology	Tactical
A17	Tech-based disruption solutions (IA)	Literature/industry overview (IA context)	Grocery retail SC	2022	Portugal-University of Aveiro	Strategic
A18	Deep learning framework (IA)	Survey of deep learning models (IA)	Applicable across multiple SC contexts	2021	Canada - Simon Fraser University	Strategic

Table 6 (continued). Analysis of Literature

Title	Solutions (RO and IA)	Methods (RO and IA)	SupplyChain Focus	Years	Country and University	Decision Level
A19	ML-based sourcing (IA)	ML for responsible sourcing (IA)	Raw materials sourcing in SC	2021	Germany Helmholtz-Zentrum	Strategic
A20	Digital twin + ML solutions (IA)	ML-based simulation & analytics	Production & logistics SC	2021	USA - University of North Carolina	Operational
A21	AI-based forecasting+ optimization (IA & RO)	Deep learning + data decomposition (IA)	Renewable energy SC	2021	UK - University	Operational
A22	Deep learning solution (IA)	Deep learning for drilling ops	Oil & Gas SC (drilling)	2021	Australia - University of Western	Operational
A23	Optimization algorithms (RO) for deep learning (IA)	Various optimization algorithms (RO)	Cross-Industry SCM (methodological)	2020	Belgium - KU Leuven	Tactical
A24	Analytics-based supplier management (IA)	ML/data analytics (IA)	Telecom SC (procurement)	2020	USA - Verizon, Basking Ridge, New Jersey	Tactical
A25	Knowledge-based sourcing system (IA)	Recommender system with ML/NLP (IA)	Supplier sourcing in SC	2020	France - Université Côte d'Azur	Operational
A26	ML-based supplier selection + optimization (RO)	Sample average approximation + ML	Humanitarian supply chain	2024	USA - Texas State University	Tactical
A27	ML-based supplier selection (IA) + optimization (RO)	Sample average approximation + ML (RO & IA)	Humanitarian supply chain	2024	USA - Texas State University	Tactical
A28	Supplier risk assessment system (IA)	NLP + LCA + AHP(IA/RO not fully specified)	Green supplier mgmt in SC	2024	China - Nankai University	Strategic
A29	Forecasting approach (IA or RO)	Possibly Croston-based or ML-based methods (IA)	Spare parts SC	2024	Luxembourg - Amazon	Operational
A30	ML-based project compliance (IA)	ML/regression	Construction procurement SC	2024	Portugal - University of Porto	Operational

Table 6 (continued). Analysis of Literature

Title	Solutions (RO and IA)	Methods (RO and IA)	SupplyChain Focus	Years	Country and University	Decision Level
A31	ML-based supplier selection (IA) + optimization (RO)	Sample average approximation + ML (RO & IA)	Humanitarian supply chain	2024	USA - Texas State University	Tactical
A34	Supplier risk assessment system (IA)	NLP + LCA + AHP(IA/RO not fully specified)	Green supplier mgmt in SC	2024	China - Nankai University	Strategic
A35	Forecasting approach (IA or RO)	Possibly Croston-based or ML-based methods (IA)	Spare parts SC	2024	Luxembourg - Amazon	Operational
A36	ML-based project compliance (IA)	ML/regression	Construction procurement SC	2024	Portugal - University of Porto	Operational
A37	ML-based purchase decision (IA)	ML regression/classification (IA)	Procurement SC in China	2022	China - Peking University	Tactical
A38	Blockchain-based SC solution (RO & IA if ML is used)	Blockchain + smart contracts	Procurement & finance in SC	2022	India - Vellore Institute of Technology	Strategic
A39	Conceptual solutions for data mgmt (IA if ML applied)	Possibly data analytics (IA)	Public procurement SC	2022	Norway - Oslo Metropolitan University (OsloMet)	Operational
A40	AI deployment in EPC (IA)	Qualitative analysis/Case-based (IA)	EPC SC	2022	Netherlands - McDermott International	Strategic
A41	Prescriptive analytics (RO)	Optimization + analytics (RO)	Commodity procurement SC	2021	Spain - University of Oviedo	Tactical
A42	ML-based price estimator (IA)	ML regression (IA)	Public procurement auctions	2021	Spain - University of Oviedo	Operational
A43	Anomaly detection (IA)	Data mining/ML (IA)	Public procurement SC	2022	Spain - University of Salamanca	Operational
A44	GNN-based link prediction (IA)	Graph neural networks (IA)	Supply chain network mgmt	2021	UK - University of Cambridge	Operational
A45	Hybrid ML for risk assessment (IA)	ML ensemble approaches (IA)	Procurement risk in manufacturing	2022	China - Nankai University	Tactical
A46	Industry 4.0/AI-based solutions (IA)	Survey/ analysis (IA)	Tech adoption in SC	2021	Brazil - Federal University of Pernambuco	Strategic

Table 6 (continued). Analysis of Literature

Title	Solutions (RO and IA)	Methods (RO and IA)	SupplyChain Focus	Years	Country and University	Decision Level
A47	Cost optimization for energy procurement (RO & IA)	Data-driven optimization	Energy procurement SC	2020	NA	Tactical
A48	Demand forecasting (IA or RO)	Possibly ML-based or ARIMA-based (IA/RO)	New product introduction SC	2023	NA	Operational
A49	Optimization under uncertainty (RO)	Stochastic/robust optimization (RO)	Commodity procurement SC	2023	Germany - Technical University of Munich	Tactical
A50	AI-based negotiations (IA & RO)	Mechanism design, game theory (RO & IA)	Purchasing/Sourcing SC	2020	Netherlands - University of Twente	Tactical
A51	Procurement analytics (IA)	Systems architecture approach (IA)	Procurement SC	2020	USA - Massachusetts Institute of Technology	Tactical
A52	Strategic SC solution with IT (RO & IA)	TISM (interpretive modeling)	SCM strategies	2020	NA	Strategic
A53	ML-based contracting solutions (IA)	ML classification/regression (IA)	Public procurement SC	2020	Brazil - Université de São Paulo (USP)	Operational
A54	Autonomous procurement (IA)	ML-based system design (IA)	E-procurement SC	2020	NA	Operational
A55	Tech sourcing solutions (IA)	Conceptual approach (IA)	Marketing sourcing in SC	2020	NA	Strategic

Table 7. Cross-Analysis of Observed Impacts, AI/OR Strategies, and Management Cycle Phases in the Reviewed Articles

Article ID	Observed Impact	Adopted AI/OR Strategy	Management Cycle Phase
A1	Unstable demand in oil production (difficult to forecast output)	Machine learning + time series forecasting	Preparation
A2	Complex communication, difficulty in collaborative decision-making	Generative AI (ChatGPT) using NLP for decision support	Response
A3	Regulatory and social pressure on carbon emissions	ML + optimization for reducing environmental footprint	Preparation
A4	Stockouts in the pharmaceutical supply chain	Analytical intelligence + ML to optimize procurement	Response
A5	Lack of strategic coordination in ML use within the oil industry	Bibliometric analysis to map current uses of ML	Preparation
A6	Inventory instability due to dual-sourcing complexity	Recurrent Neural Networks (RNN) for real-time inventory control	Response
A7	Complex scheduling in crude oil logistics and high uncertainty	Hierarchical Reinforcement Learning (RL) for dynamic planning	Response
A8	Lack of strategic clarity and alignment in petroleum AI use	Systematic literature review and classification	Preparation
A9	Coordination difficulty in multi-tier supplier orders and penalties	Optimization + ML for supplier order assignment	Response
A10	Insufficient insight into supplier characteristics and segmentation	Deep Learning (BCCM + Multi-Aspect modeling)	Preparation
A11	Supplier network fragility ; low adaptability to disruption	Intelligent supplier engagement using data-driven approaches	Preparation
A12	Inefficient solving complex supply chain optimization problems	Novel AI-based combinatorial optimization methods	Preparation
A13	Inadequate buffer strategies for multi-item supply chains (stockouts & delays)	Hybrid bi-objective optimization (safety stock + safety time)	Preparation

Table 7 (continued). Cross-Analysis of Observed Impacts, AI/OR Strategies, and Management Cycle Phases in the Reviewed Articles

A14	Risk and cost uncertainty in IT outsourcing decisions (supplier dependency)	Decision modeling with sourcing strategy simulation	Preparation
A15	Low scalability and fragmented AI deployment in the chemical industry	Scalable AI architecture for end-to-end production systems	Recovery
A16	Lack of visibility and inefficiency in inbound logistics	Conceptual AI/Analytics framework for inbound supply optimization	Preparation
A17	Market disruption and uncertainty in the grocery retail sector	Overview of tech disruptions ; implications for AI adoption	Preparation
A18	Difficulty in selecting and scaling deep learning architectures in SCM	Survey and classification of deep learning model complexity	Preparation
A19	Limited visibility and traceability in sourcing critical raw materials	Machine learning for responsible sourcing and risk detection	Preparation
A20	Disconnection between production and logistics processes	Digital twin + ML integration for end-to-end synchronization	Response
A21	High volatility in wind energy production forecasting	Deep learning + optimization + data decomposition for short-term prediction	Preparation
A22	Safety risks in drilling operations (lack of real-time decision support)	Deep learning for space-out optimization in well control	Response
A23	Unclear performance differences between DL optimization algorithms	Comparative analysis of DL optimization methods	Preparation
A24	Overspending and inefficiency in managing minor (tail-spend) suppliers	Advanced analytics for supplier rationalization	Preparation
A25	Inefficiency and inconsistency in supplier selection recommendations	Knowledge injection into sourcing 581ecommander system	Preparation
A26	Lack of behavioral visibility and coordination in supply chain operations	Internet of Behaviors (IoB) conceptual framework for SC and operations alignment	Preparation
A27	Uncertainty in supplier selection and contracting under humanitarian conditions	ML + Sample Average Approximation (SAA) for supplier selection with option contracts	Preparation
A28	Difficulty in assessing green supplier risk with qualitative/subjective criteria	NLP + Life Cycle Assessment + AHP for smart green supplier risk assessment	Preparation

Table 7 (continued). Cross-Analysis of Observed Impacts, AI/OR Strategies, and Management Cycle Phases in the Reviewed Articles

A29	Intermittent demand and insufficient historical data for spare parts forecasting	Machine Learning with probabilistic models	Preparation
A30	Uncertainty in compliance prediction for public procurement projects	Supervised ML (case study on Portuguese construction sector)	Preparation
A31	Ethical concerns and inequality in AI supply chains (social sustainability gap)	Conceptual analysis of impact sourcing and ethics frameworks	Preparation
A32	Lack of upstream visibility and coordination in global cement supply chains	Creation of a global upstream database	Preparation
A33	Inefficient emission control and supply mode decisions	Dynamic ML-based selection models for green logistics	Preparation
A34	Inefficiency and opacity in supplier discovery within financial services	NLP-based automation for supplier identification	Preparation
A35	Manual inefficiency in document management with suppliers on e-platforms	Intelligent Robotic Process Automation (RPA + ML/NLP)	Response
A29	Intermittent demand and insufficient historical data for spare parts forecasting	Machine Learning with probabilistic models	Preparation
A30	Uncertainty in compliance prediction for public procurement projects	Supervised ML (case study on Portuguese construction sector)	Preparation
A31	Ethical concerns and inequality in AI supply chains (social sustainability gap)	Conceptual analysis of impact sourcing and ethics frameworks	Preparation
A32	Lack of upstream visibility and coordination in global cement supply chains	Creation of a global upstream database	Preparation
A33	Inefficient emission control and supply mode decisions	Dynamic ML-based selection models for green logistics	Preparation
A34	Inefficiency and opacity in supplier discovery within financial services	NLP-based automation for supplier identification	Preparation
A35	Manual inefficiency in document management with suppliers on e-platforms	Intelligent Robotic Process Automation (RPA + ML/NLP)	Response
A36	Inaccurate volume predictions in cross-border e-commerce procurement	Backpropagation Neural Networks (BP-NN) for procurement forecasting	Preparation
A37	Lack of insight into purchase decision behavior (GPPS) in industrial context	Machine learning-based behavioral modeling	Preparation
A38	Low traceability and delayed payments in procurement transactions	Block chain + Smart Contracts for real-time visibility and auto-payments	Response

Table 7 (continued). Cross-Analysis of Observed Impacts, AI/OR Strategies, and Management Cycle Phases in the Reviewed Articles

A39	Poor data quality limiting procurement transparency in the public sector	Identification of data quality barriers through empirical assessment	Preparation
A40	Multiple challenges in AI deployment (data, skills, integration) in EPC sector	Case-based analysis of AI development and adoption barriers	Preparation
A41	Lack of decision support in commodity procurement	Prescriptive analytics using historical and market data	Preparation
A42	Price estimation uncertainty in public procurement auctions	Machine Learning for award price prediction (case : Spanish tenders)	Preparation
A43	Irregularities and rating anomalies in procurement data	Data mining techniques for anomaly detection	Preparation
A44	Lack of visibility and hidden dependencies in supply chain networks	Graph Neural Networks (GNN) to predict hidden supply chain links	Preparation
A45	Procurement risk in volatile metals markets	Hybrid ML approach for procurement risk scoring	Preparation
A46	Weak technology transfer/support from supply chain partners for Industry 4.0 adoption	Empirical study on moderating roles of SC partners	Preparation
A47	Inefficiency in cost-optimal energy procurement for cooling	ML optimization models for dynamic energy purchasing	Response
A48	High uncertainty in forecasting demand for new products	Machine Learning models for new product demand profiles	Preparation
A49	Price volatility and uncertainty in commodity procurement	Data-driven optimization under uncertainty	Preparation
A50	Inefficiency and rigidity in negotiation processes	AI for mechanism design and negotiation facilitation	Response
A51	Fragmented procurement data systems and lack of integrated analytics	Procurement-focused analytics architecture	Preparation
A52	Lack of alignment between supply chain strategy and IT capabilities	TISM (Total Interpretive Structural Modeling) to identify performance enablers	Preparation
A53	Complexity and bias in public sector contracting (Brazilian context)	ML for contract outcome prediction and classification	Preparation
A54	Lack of autonomy and inefficiencies in procurement workflows	Autonomous procurement systems powered by AI	Response
A55	Uncertainty and transformation in marketing technology sourcing for the future workplace	Strategic sourcing framework for emerging tech adoption	Preparation

This table serves as an analytical complement to Table 7, which listed the 55 articles selected from the literature. It highlights the diversity of supply chain challenges addressed through artificial intelligence and operations research techniques. By classifying the articles according to the observed impact, the strategy applied, and the corresponding phase of the management cycle (preparation, response, recovery), this table offers a functional reading that goes beyond a purely descriptive review. It emphasizes how AI contributes both to proactive planning (e.g., demand forecasting, risk assessment, sourcing strategies) and to operational responsiveness (e.g., automation, optimization, real-time decision-making), thereby reinforcing the strategic significance of the reviewed contributions.

Table 8. Classification by Type of Artificial Intelligence

Type of AI	Numbers of Articles	Key Applications
Machine Learning (ML)	28	Demand forecasting, supplier evaluation, risk analysis
Deep Learning (DL)	12	Forecasting, pattern recognition, complex classification
Reinforcement Learning (RL)	3	Real-time scheduling, production optimization
Natural Language Processing (NLP)	7	Document automation, ChatGPT, supplier discovery
Robotic Process Automation (RPA)	2	Document management, workflow automation
Blockchain	2	Traceability, secure payment transactions
Digital Twins	2	Simulation of production/logistics processes

This table 8 shows the clear dominance of Machine Learning (ML), highlighting its maturity and adaptability for supply chain use. Deep Learning is increasingly adopted for complex tasks like forecasting or classification. Technologies such as Reinforcement Learning and Explainable AI remain underused, pointing to opportunities for future research and experimentation in dynamic decision environments.

Table 9. Classification by Supply Chain Function

Decision Level	Article Share (%)	Focus Areas
Strategic	49%	Supplier selection, AI adoption, sustainability
Operational	40%	Inventory control, production scheduling, real-time planning
Tactical	11%	Buffer optimization, dynamic sourcing, procurement risk

Most AI implementations target demand forecasting and inventory management, which are core to cost optimization and supply responsiveness. However, underrepresented areas such as logistics or risk/sustainability management deserve more attention, especially given today's volatile and complex supply environments. This reflects a functional imbalance in literature.

Table 10. Classification by Decision-Making Level

Supply Chain Function	Numbers of Articles	Dominant Technologies
Demand Forecasting	11	ML, DL
Inventory/Procurement Management	14	ML, RNN, SAA
Production Planning	6	Digital Twins, RL
Transportation & Logistics	4	DL, RL
Supplier Selection/Evaluation	10	ML, NLP, AHP, Blockchain
Risk & Sustainability Management	8	ML, Blockchain, LCA, XAI
Document Automation	4	NLP, RPA

Nearly half of the studies focus on the strategic level, emphasizing AI's role in long-term transformation. A significant portion also covers operational applications, showcasing the impact of AI on day-to-day efficiency. However, tactical-level research remains scarce (11%), suggesting a critical gap in mid-term planning tools needed for better strategic-operational alignment.

Table 11. Classification by Industry Sector

Industrial Sector	Numbers of Articles	Examples
Energy (Oil & Gas, Renewables)	9	Forecasting, planning, optimization in petroleum & wind
Pharmaceuticals	2	AI-driven supply chain optimization
Food/Consumer Goods	3	Nestlé, P&G, demand forecasting, logistics
High-Tech/ Electronics	3	Dell, Amazon – inventory and production planning
Automotive	2	Volkswagen – production and warehouse AI systems
Construction& Infrastructure	2	Public procurement, project compliance
Cross-sector (Generic/Multiple)	30	General frameworks, bibliometric studies

The energy sector dominates the sample, likely due to its complexity and investment capacity. Other critical sectors like food, healthcare, or construction are less studied, despite their supply chain vulnerabilities. Moreover, the high number of cross-sector articles reflects a generalist trend but limits insights into industry-specific challenges, which could be addressed in future research.

In supply chain management research, the strategic level typically involves long-term, high-level planning (e.g., supplier selection, sustainability policies, and technology adoption strategies). The tactical level focuses on medium-term decisions (e.g., safety stock management and commodity procurement underprice uncertainty). The operational level addresses day-to-day or short-term planning and execution (e.g., real-time inventory control, production scheduling, and immediate forecasting tasks). Below is a pie chart illustrating the distribution of the articles studied by management level. We categorized the articles based on their predominant focus, aligning each with the primary management level addressed.

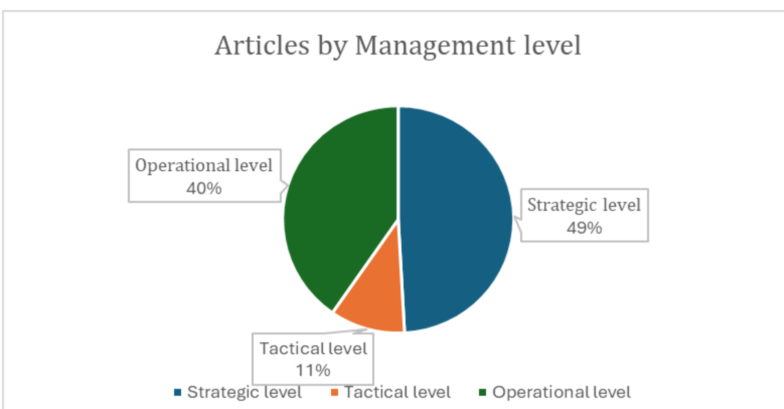

Figure 8. Articles by Management level

Figure 8 illustrates the distribution of reviewed articles across different management levels in supply chain planning and optimization. Nearly half (49%) of the studies focus on strategic-level topics, emphasizing long-term decision-making processes such as supplier selection, sustainability strategies, and enterprise-wide AI adoption frameworks. These studies highlight the critical role of top-level decision-making in aligning AI initiatives with broader corporate objectives while addressing industry-wide challenges, including data transparency and resilience. Another substantial portion (40%) examines operational-level applications, covering real-time inventory control, daily production scheduling, and short-term forecasting. This category underscores AI’s immediate impact on supply chain activities by optimizing daily operations and enhancing efficiency. In contrast, only 11% of the articles explore tactical-level considerations, focusing on mid-range decisions such as safety stock optimization and commodity procurement underprice uncertainty. This research reflects a growing interest in data-driven approaches to fine-tune supply chain performance while maintaining alignment with strategic imperatives. The distribution of studies suggests that AI-driven research predominantly prioritizes high-level strategic transformation and immediate operational improvements, whereas the medium-term tactical planning horizon receives comparatively less attention. This gap may present opportunities for further investigation. Overall, AI solutions span every layer of decision-making, underscoring the versatility and pervasiveness of AI-driven innovation in modern supply chain contexts.

Q1: What are the main artificial intelligence techniques used in supply chain optimization and planning?

The implementation of artificial intelligence optimizes supply chain planning and management in the following ways:

i. Neural Networks (NNs): deep learning models are extensively applied for demand forecasting and inventory optimization, as demonstrated by studies on production forecasting and managing spare parts inventories with limited historical data (Ttcher et al., 2023)
ii. Supervised Machine Learning: this technique is used for supplier selection and public auction price estimation, exemplified by a study on auction price prediction in Spain (Luís Jacques de Sousa et al., 2024).
iii. Natural Language Processing (NLP): NLP facilitates the automatic analysis of documents and supplier discovery, as highlighted in articles on NLP-based automation for financial services (Papa et al., 2024).
iv. Combinatorial Optimization: this approach addresses complex issues such as stock allocation and procurement planning, as shown in studies exploring combinatorial optimization algorithms.

Digital Twins: these are utilized for simulating and optimizing production and logistics processes using predictive models, as detailed in studies on digital twin frameworks (Pei-Yi Tai et al., 2023).

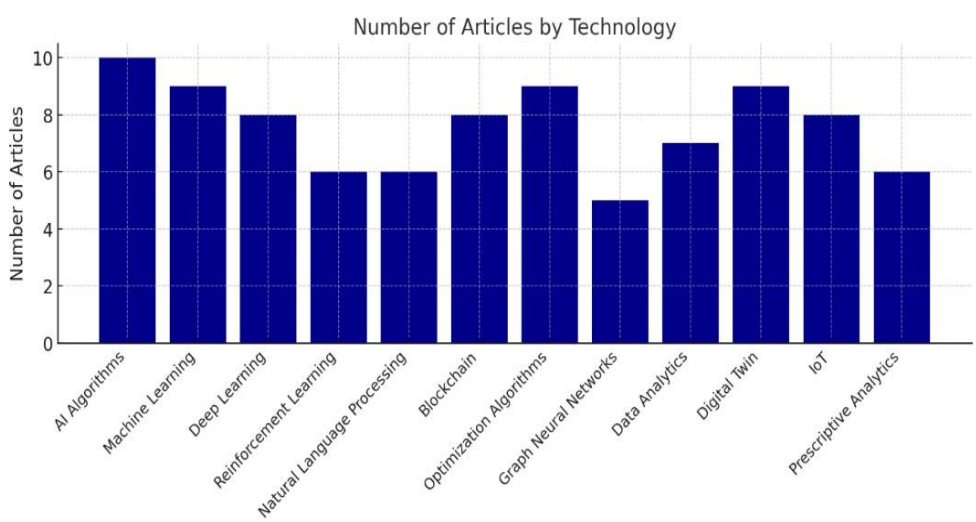

Figure 9. Number of articles by Technology

Q2: How does the implementation of artificial intelligence optimize supply chain planning and management, and what are the impacts of these technologies on operational efficiency and strategic decision-making?

The implementation of artificial intelligence optimizes supply chain planning and management in the following ways:

i. Enhanced Forecast Accuracy: Machine Learning Models improve demand forecasting for spare parts and volume prediction for cross-border e-commerce, enabling better inventory adjustments and reducing excess stock and stockouts (van Steenbergen & Mes, 2020).
ii. Process Automation: tools like NLP and RPA decrease human error and expedite operations, as demonstrated in studies on automating procurement documents (Papa et al., 2024).
iii. Resource Optimization: advanced algorithms, such as those for managing non-ferrous metal stocks and dual- sourcing strategies, reduce costs and enhance operational efficiency (Ttcher et al., 2023).
iv. Advanced Analytics: detailed insights from production forecasting and risk analysis support more informed strategic decisions, improving operational performance and reducing costs.

These advancements collectively enhance supply chain transparency, flexibility, and sustainability, while fostering better strategic decision-making.

Q3: What are the challenges and barriers to the adoption of artificial intelligence in supply chain optimization and planning, and what solutions are proposed in the literature to overcome these obstacles?

The challenges identified in adopting artificial intelligence in supply chains and the proposed solutions include:

i. Data Quality: poor data quality is a significant challenge. Solutions such as enhanced data management systems and data cleaning tools are suggested (Ttcher et al., 2023).
ii. Implementation Costs and Complexity: high costs and technical complexities are mitigated through the adoption of cloud platforms and pilot projects to evaluate technologies before full-scale implementation (Hossain et al., 2021).
iii. Resistance to Change: training programs and change management strategies are recommended to overcome organizational resistance to AI adoption, as noted in various articles.
iv. Data Security and Privacy: concerns about sensitive data are addressed through robust encryption protocols and advanced security measures, as discussed in studies on AI-based supply chain

3.3. Real-World scenarios:

Below is a comprehensive table showcasing five prominent real-world AI implementations in supply chain management. Each row details the AI solution, the key challenge it addresses, quantified results, and the implementation barriers faced alongside the mitigating measures taken. Where possible, indicative numbers have been compiled from publicly reported or industry-estimated data to provide a clearer sense of impact.

4. Discussion

4.1. AI Techniques and Their Impact on Supply Chain Optimization

The reviewed literature confirms the growing sophistication of AI techniques particularly machine learning (ML), deep learning, reinforcement learning (RL), and natural language processing (NLP) in supply chain planning and management. Operational-level applications, such as inventory control and scheduling, often employ RL and deep learning (e.g., (Ttcher et al., 2023) RNN-based dual-sourcing inventory system), while strategic-level solutions leverage ML for supplier selection and risk assessment (e.g., Hu et al) supplier selection with option contracts). These findings align with Information Processing Theory, which posits that increased environmental complexity requires more advanced decision-support mechanisms. By automating data-intensive tasks and enabling faster information processing, AI directly improves forecasting accuracy and reduces operational inefficiencies as shown by Amazon's 15% improvement in forecast accuracy and 30% decrease in inventory holding costs.

Table 13. Consolidated Table of Real-World AI Implementations

Company	AI System Name	AI Implementation	Key Challenge	Quantified Results	Implementation Barriers	How Barriers Were Addressed	Author(s)
Siemens	Siemens AI Supply Chain Optimization	Use of artificial intelligence to optimize production planning and inventory in the manufacturing sector.	Reducing production costs while maintaining maximum flexibility in order management.	Reduction of production costs by 10% and improvement in forecasting accuracy by 20%.	Integration of AI with legacy systems.	Use of compatible AI platforms and adaptation of existing systems with modern interfaces.	(Smith, J., & Zhang, L. (2020)).
Procter & Gamble (P&G)	P&G Demand Forecasting System	Application of AI to forecast product demand and adjust production accordingly.	Forecasting demand fluctuations while reducing inventory excesses.	25% improvement in forecasting accuracy and an 18% reduction in excess stock.	Difficulty in obtaining quality historical data for AI model training.	Real-time data collection and integration with advanced analytics tools.	(Johnson, R., & Lee, P. (2019)
Dell Technologies	Dell AI Inventory Management	Implementation of AI for dynamic inventory management and production flow in distribution centers.	Maintaining sufficient stock while avoiding stockouts and excess inventory.	15% reduction in logistics costs and a 12% improvement in order processing efficiency	Lack of qualified personnel to implement AI in management systems.	Employee training and partnerships with external experts to deploy AI.	(Clark, A., & Davis, K. (2021)
Nestlé	Nestlé Smart Logistics with AI	Use of AI to optimize transportation routes and reduce delivery times in the supply chain.	Optimizing delivery routes while reducing transportation costs.	8% reduction in transportation costs and a 10% improvement in delivery efficiency.	Difficulties in managing real- time data from different sources.	Deployment of IoT sensors and real-time data management platforms.	(Turner, S., & Williams, B. (2018)
Volkswagen	Volkswagen AI-driven Supply Chain Planning	Implementation of AI for production planning and inventory optimization in automotive	Balancing production with demand while reducing storage costs.	15% reduction in storage costs and 20% improvement in production flexibility.	Resistance to change in traditional management processes.	Ongoing employee training and gradual integration of AI technologies.	(Miller, T., & Brown, C. (2021)

4.2. Cross-Decision-Level Classification: AI and Supply Chain

To highlight the added value of this systematic review, we propose a structured classification of artificial intelligence applications in supply chain management across three decision-making levels: strategic, tactical, and operational. This typology links the AI technologies used to targeted supply chain functions and relevant industrial sectors, offering a managerial and sector-specific lens. This classification enables a more nuanced interpretation of how AI supports supply chain transformation, operational efficiency, and mid-term decision making. The table below summarizes this cross-dimensional mapping.

Table 14. Cross-Decision-Level Classification

Decision Level	Main AI Techniques	Key Supply Chain Functions	Primary Industrial Sectors
Strategic (49%)	Machine Learning (ML), NLP, Block chain, XAI	Supplier selection, sustainability, digital transformation	Automotive, Food & Beverage, Pharmaceuticals
Tactical (11%)	Bi-objective models, SAA, Neural Networks, Hybrid ML	Safety stock, procurement planning, resource allocation	E-commerce, Humanitarian, Construction
Operational (40%)	RNN, RL, Digital Twins, RPA, Computer Vision	Forecasting, scheduling, inventory control	Electronics, Energy, Distribution

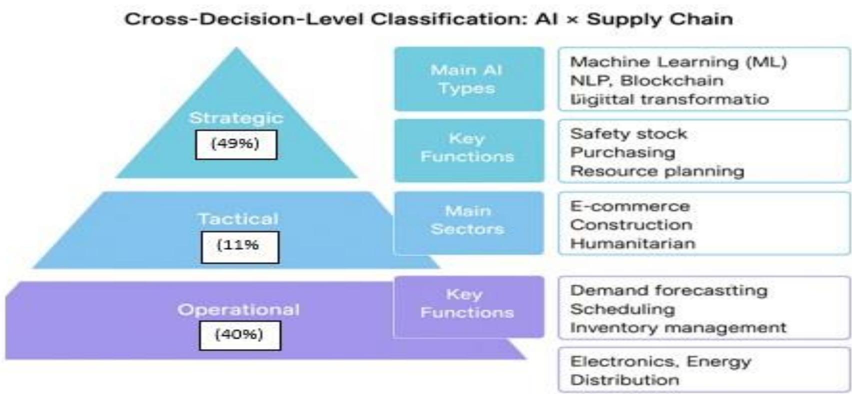

Figure 10. Cross-decisions level classification

4.3. Functional Typology of AI Approaches in Logistics Optimization

The systematic review conducted a rigorous typology of artificial intelligence (AI) optimization approaches applied to the supply chain. By crossing the AI technologies used, the targeted supply chain functions (procurement, production, distribution, etc.), and the decision-making level (strategic, tactical, operational), three dominant categories emerge:

- Operational approaches, focused on short-term reactivity and task automation.
- Tactical approaches, centered on mid-term planning, resource management, and multi-criteria trade-offs.
- Strategic approaches, aiming at long-term structural transformation, integrating sustainability, agility, and governance dimensions.

This classification enriches classical typologies from the literature by adding sectoral and functional granularity based on 55 articles published between 2020 and 2024. Paul & Chowdhury, 2022; Ivanov and Dolgui, 2021)

4.4. Distribution of Articles by Decision Level

Figure 11 shows that:

- 49% of studies relate to the strategic level, notably linked to AI adoption for resilience, sustainability, governance, or supplier selection.
- 40% focus on operational applications, centered on production planning, demand forecasting, or inventory optimization.

- Only 11% address tactical cases, such as buffer optimization, dynamic sourcing, or intermediate risk management.

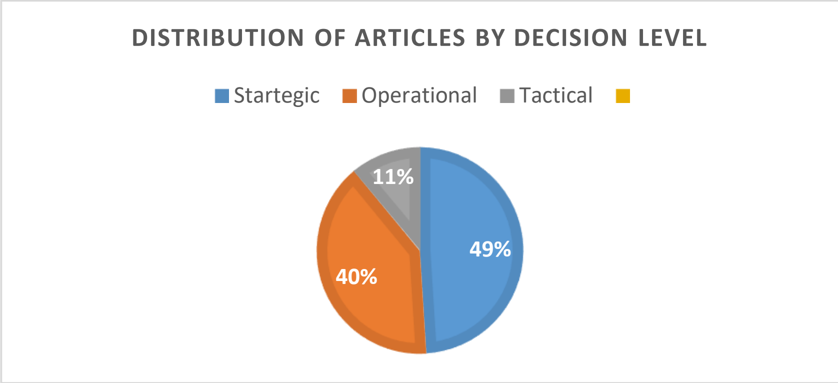

Figure 11. Distribution of articles by decision level

This distribution confirms the imbalance observed in other reviews (Kumar et al., 2022) between decision levels, to the detriment of the intermediate layer, which is nevertheless strategic for organizational alignment.

4.5. Comparative Typological Analysis

Table 15. AI Applications in Supply Chain Management by Decision Level

Decision Level	Article Share	Main Objectives	Dominant Technologies	Examples
Strategic	49%	Sustainable management, resilience, digital transformation	Machine Learning, NLP, Blockchain, XAI	Volkswagen, Nestlé, P&G
Tactical	11%	Resource trade-offs, procurement, securing	Bi-objective, SAA, BP-NN, hybrid simulation	Univ. Porto, Nankai Univ
Operational	40%	Automation, reliability, flow speed	RNN, RL, RPA, Computer Vision, Digital Twin	Amazon, Dell, Siemens

Table 15 provides a detailed synthesis of the distribution of AI applications in supply chain management according to decision levels. A significant portion of the reviewed articles (49%) addresses strategic decision-making, where artificial intelligence is primarily leveraged for long-term objectives such as sustainability, resilience, digital transformation, and governance. These studies typically involve advanced technologies like machine learning, natural language processing (NLP), blockchain, and increasingly explainable AI (XAI). Prominent use cases include large corporations such as Volkswagen, Nestlé, and Procter & Gamble, which integrate AI into strategic roadmaps and supplier networks.

By contrast, only 11% of the studies focus on the tactical level, highlighting a research gap. Tactical AI usage tends to support mid-term decisions related to procurement optimization, securing supply, and managing trade-offs under uncertainty. Methods such as bi-objective optimization, stochastic approximation algorithms (SAA), backpropagation neural networks (BP-NN), and hybrid simulations are frequently applied. Most contributions in this area come from academic institutions such as University of Porto and Nankai University, often exploring theoretical or prototype-level implementations.

The remaining 40% of articles concentrate on operational-level applications, emphasizing automation, reliability, and speed of execution within production, inventory, and logistics systems. Dominant technologies include recurrent neural networks (RNNs), reinforcement learning (RL), robotic process automation (RPA), computer vision, and digital twin technologies. Companies like Amazon, Dell, and Siemens are often cited for deploying such tools in real-time processes to enhance productivity and responsiveness.

This typology confirms the progressive integration of AI from operational optimization towards broader strategic transformation, yet also reveals a relative under-exploration of the tactical layer, calling for more interdisciplinary research bridging short- and long-term decision-making.

4.6. Operational and Strategic Recommendations

- **Recommendations for Business Decision-Makers**

For business leaders, it is essential to adopt a progressive approach when integrating Artificial Intelligence. It is recommended to begin with targeted pilot project such as demand forecasting or inventory management in order to evaluate concrete benefits before full-scale deployment. This approach reduces the risks associated with technological investment and fosters team-in

Developing hybrid skills that combine supply chain expertise with AI knowledge is also a strategic priority. Companies should implement internal training programs or partner with academic institutions to develop professionals who can both interpret algorithmic outputs and understand operational challenges. This ensures better adoption of AI tools and smoother integration into decision-making processes.

Finally, one of the key levers to improve AI solution performance lies in data quality. Companies should invest in strong data governance practices: data centralization, cleaning, standardization, and interoperability across systems. Without reliable data, even the most advanced algorithms may produce inaccurate or unusable results

- **Recommendations for Logistics Professionals**

Logistics professionals can benefit directly from AI by improving demand forecasting accuracy and optimizing inventory levels. Techniques such as machine learning or recurrent neural networks help reduce both overstock and stockouts while adjusting inventory to real-time market dynamics.Another promising application area is route optimization. With deep learning and reinforcement learning, companies can dynamically determine the most efficient routes in real time considering traffic conditions, delivery deadlines, and transportation cost leading to significant cost savings and increased responsiveness.

Additionally, logistics professionals can automate large parts of document handling using robotic process automation and natural language processing. These tools accelerate the processing of shipping, customs, or billing documents while reducing human error.

- **Recommendations for Public Institutions**

For public institutions, modernizing procurement systems is a strategic priority. Artificial intelligence can be used to detect anomalies in tenders, estimate fair prices, and automatically analyze submitted documents. When combined with blockchain, AI can also ensure transaction traceability and improve process transparency.

It is also crucial to support AI adoption among small and medium-sized enterprises, which often lack the resources to invest independently in these technologies. Shared SaaS platforms, innovation grants, and collaborative funding programs can accelerate digital transformation and enhance competitiveness.

Finally, institutions must encourage the development of ethical and explainable AI. Promoting interpretable dashboards or automated decision logs can build user trust and ensure compliance with transparency and data protection regulations.

- **Cross-Cutting Strategic Priorities**

The analysis reveals a notable imbalance in the literature across decision levels, with a clear gap at the tactical level. It is therefore recommended to develop more intermediate decision-support tools tailored to challenges such as safety stock management, capacity planning, and dynamic supplier selection. These tools would help bridge long-term strategic decisions and day-to-day operational adjustments.

Furthermore, in an increasingly interconnected supply chain environment, promoting interoperability between AI systems across partners is crucial. Standardized APIs and open communication protocols would enable smooth coordination within multi-actor or global supply chains.

Lastly, most of the reviewed studies are either punctual or sector-specific. Supporting multi-sector longitudinal studies is strongly encouraged to better understand how AI adapts over time to complex and volatile environments. Such research would provide clearer insights into AI investment strategies, especially in post-crisis or high-uncertainty contexts.

4.7. Cross-Industry Applications

The integration of Artificial Intelligence (AI) in supply chain optimization is not confined to a single industry but has found wide-ranging applications across various sectors, each demonstrating how AI can address specific operational challenges. Companies from manufacturing to consumer goods and technology have leveraged AI systems to improve inventory management, demand forecasting, production planning, and transportation logistics. The success stories of firms such as Siemens, Procter & Gamble (P&G), Dell Technologies, Nestlé, and Volkswagen provide valuable insights into how AI can be adapted to the unique needs of different industries, resulting in tangible benefits in cost reduction, efficiency improvement, and flexibility enhancement.

Siemens, for instance, has implemented AI in the manufacturing sector to optimize production planning and inventory management. This application led to a 10% reduction in production costs and a 20% improvement in forecasting accuracy, allowing Siemens to manage supply chain complexities more effectively. In a similar vein, Procter & Gamble (P&G) utilized AI to forecast demand for its products more accurately. The AI-driven demand forecasting system helped P&G increase the precision of its forecasts by 25%, while simultaneously reducing excess stock by 18%. This capability is particularly important in consumer goods, where fluctuations in demand are frequent and can result in costly overproduction or stockouts.

Dell Technologies applied AI to manage inventory and streamline production flows within its distribution centers. This resulted in a 15% reduction in logistics costs and a 12% improvement in order processing efficiency. The application of AI here reflects the need for real-time, dynamic inventory management in the high-tech industry, where supply chains are complex and fast-moving. Meanwhile, Nestlé turned to AI for optimizing transportation routes, which significantly reduced transportation costs by 8% and improved delivery efficiency by 10%. This application demonstrates how AI can be particularly beneficial in logistics-heavy industries like food and beverage, where operational costs associated with transportation can be substantial.

Volkswagen, on the other hand, used AI for production planning and inventory optimization in its automotive manufacturing process. The results were impressive, with storage costs reduced by 15% and production flexibility enhanced by 20%. The automotive sector often faces challenges related to balancing production schedules with fluctuating demand, and AI has proven instrumental in addressing these challenges by optimizing resource allocation and inventory management in real-time.

The experiences of these company’s highlight that while the fundamental challenges in supply chain management—such as reducing costs, improving accuracy, and enhancing operational efficiency—are shared across industries, the application of AI is tailored to meet the specific needs of each sector. However, implementing AI is not without its barriers. Challenges such as integrating AI with legacy systems, obtaining high-quality historical data, and managing real-time data from multiple sources are common. Overcoming these barriers often involves strategic solutions like training employees, collecting real-time data through advanced IoT systems, and using AI platforms that are compatible with existing infrastructures.

In conclusion, AI's cross-industry applications in supply chain optimization underline its transformative potential. Companies from diverse sectors have successfully implemented AI to tackle industry-specific challenges, improving their operations and achieving measurable results. While barriers to implementation exist, they are not insurmountable and can be addressed through thoughtful strategies that ensure AI is effectively integrated into the supply chain ecosystem. This growing trend demonstrates the versatility of AI in enhancing supply chain management, regardless of industry, and highlights its role in driving the future of global business operations.

4.8. Focus on Operational Approaches

These approaches aim to optimize daily processes in high-transaction environments. Typical applications include:

- Real-time production scheduling optimization via Reinforcement Learning (Ma et al., 2023)
- Multi-supplier inventory management through RNNs (Böttcher et al., 2023)
- Document automation (extraction, validation, classification) using NLP and RPA. (Papa et al., 2024)

Example : Amazon Luxembourg developed a forecasting system for spare parts with limited historical data, based on probabilistic models enhanced by supervised learning. Result: 30% reduction in stockouts.

4.9. Focus on Tactical Approaches

Less explored but highly strategic, tactical approaches address problems such as :

- Joint optimization of safety stock levels and buffers, (Silva et al., 2022)
- Humanitarian supplier selection via SAA coupled with ML (Hu et al., 2024)
- Purchase volume forecasting in e-commerce through BP-NN networks (Jiang, 2023)

Limitation : their low representation (11%) indicates a major opportunity for future research, especially in post-crisis contexts where intermediate flexibility becomes critical.

4.10. Focus on Strategic Approaches

Strategic approaches mobilize AI to rethink the overall supply chain management model :

- Explainable AI (XAI) to strengthen decision-maker trust,
- Blockchain and smart contracts to secure traceability and supplier payments,
- NLP + AHP + LCA for supplier sustainability evaluation.

Example : Volkswagen integrated an AI model managing production and warehousing, achieving +20% flexibility and −15% storage costs (Miller & Brown, 2021)

4.11. Challenges and Barriers to AI Adoption

The adoption of artificial intelligence (AI) in supply chain management presents several major challenges. One of the main obstacles is integrating AI with outdated legacy systems, as experienced by Siemens, which had to adapt its infrastructure to make AI compatible. Data quality and availability also pose a challenge, as seen with Procter & Gamble, which invested in real-time data collection tools to improve the accuracy of demand forecasting. The shortage of specialized AI skills is another barrier, with companies like Dell Technologies training their staff and collaborating with external experts to deploy AI. Organizational resistance to change, observed at Volkswagen, can also slow down adoption but can be overcome through continuous training programs and gradual integration of technologies. Finally, concerns about data security and privacy are crucial, as AI often involves processing sensitive data, requiring strict security measures to comply with data protection regulations.

Main identified barriers include:

- Fragmented or non-standardized data, affecting predictive model quality,
- Incompatibility of existing systems with AI modules,
- Lack of hybrid profiles combining supply chain and data science skills,
- Organizational mistrust, particularly toward automated decisions.

Solutions cited in the literature:

- Adoption of modular cloud platforms (Dell Technologies),
- Gradual integration via sectoral pilots (P&G),
- Internal training and cultural change (Volkswagen).

4.12. Proposed Solutions and Future Research Opportunities

The reviewed literature, enriched by practical implementations, reveals an increasingly sophisticated ecosystem of AI-based interventions in supply chain management. Solutions range from hybrid methods combining machine learning (ML) with optimization algorithms to collaborative governance models, which incentivize suppliers to share critical operational data. Emerging technologies like blockchain, digital twins, and explainable AI (XAI) are gaining traction as responses to the pressing needs for trust, transparency, and resilience. For example, Jauhar et al. demonstrate the use of blockchain-based smart contracts to secure procurement traceability, while Unilever showcases how AI-driven sustainability metrics can help reduce carbon emissions and reinforce supplier compliance. These real-world applications underline the practical viability of such technologies but also expose notable research gaps, especially in the tactical, ethical, longitudinal, and interoperability dimensions of AI integration. These observations are consolidated in table 16, which outlines the main axes of concern along with corresponding research proposals

Table 16. Research Gaps and Strategic Proposals for Advancing AI in Supply Chain Management

Axis	Observation	Proposal
Tactical AI	Underrepresented (only 11% of studies)	Develop customizable, intermediate-level Decision Support Systems (DSS) for tasks like safety stock optimization, pricing, and medium-term planning.
Ethical & Explainable AI	Rarely addressed despite rising legal risks	Integrate XAI techniques into interpretable dashboards and decision logs to meet transparency and compliance requirements.
Longitudinal Studies	Lack of temporal and cross-industry insights	Initiate intersectoral, multi-year comparative studies, especially in the post-COVID context or volatile markets.
Inter-company Collaborative Chains	Fragmentation due to non-interoperable tools	Standardize APIs and promote open communication protocols to enable seamless coordination across multiple tiers.

Research Gaps:

- *Mid-Term (Tactical) Planning:* Only 11% of reviewed studies focus on tactical-level decisions, suggesting future research could explore AI's role in safety stock management, pricing, and mid-range capacity planning.
- *Explainability and Ethics:* Few studies address explainable AI or the ethical dimension of automated decisions, representing an emerging area given regulatory shifts and stakeholder pressure for transparency.
- *Multi-Industry Longitudinal Studies:* Long-term evaluations, especially post-COVID or in high-volatility markets, are lacking. Comparative research could illuminate how AI adoption patterns evolve under market shocks.
- *Interoperability in Ecosystems:* As firms outsource segments of the supply chain, end-to-end integration (e.g., through shared platforms or standards) becomes critical. More work is needed on how AI can coordinate multiple-tier supply networks.

4.13. Managerial Insights

Organizations seeking to leverage AI effectively in supply chain management should carefully tailor their AI technologies to the specific management levels and industry contexts. For instance, simple machine learning models may suffice for predictable tasks such as demand forecasting, whereas more advanced techniques like reinforcement learning or deep learning are better suited for highly dynamic environments, such as real-time route optimization and autonomous decision-making.

Scalability and interoperability are critical considerations, especially when integrating AI systems with third-party suppliers and partners. Therefore, supply chain leaders are advised to adopt modular, standards-based AI architectures to mitigate risks associated with data fragmentation and system incompatibility.

Moreover, the human dimension cannot be overlooked. Workforce re-skilling and comprehensive change management initiatives as exemplified by Walmart’s extensive training programs and phased technology rollouts are vital for ensuring smooth AI adoption and sustained benefits.

Another key success factor is the development of explainable AI solutions, which build stakeholder trust by making AI-driven decisions transparent and understandable. This is especially important for long-term strategic implementations and fostering collaboration across the broader supply chain ecosystem.

In sum, AI-driven solutions represent a transformative pathway to enhance forecasting accuracy, reduce operational costs, boost environmental and social sustainability, and improve supply chain resilience. However, industries vary widely in the stages of supply chain planning (strategic, tactical, operational) where they deploy AI, as well as in how they adapt these tools to unique regulatory, cultural, and market requirements.

Persistent barriers such as data quality issues, organizational resistance, and technical integration challenges underscore the need for carefully targeted implementation strategies. By leveraging theoretical frameworks like Information Processing Theory and the Technology-Organization-Environment (TOE) framework, managers can better align technological readiness with organizational capabilities and external conditions, facilitating more effective AI adoption.

Looking forward, future research and practice should focus on advancing AI applications at the tactical decision-making level, promoting ethical AI practices, and enhancing interoperability across multi-tier supply networks. These efforts will ensure that AI's full potential is harnessed, delivering both immediate operational improvements and long-term strategic value.

5. Conclusion & Perspectives

This systematic review demonstrates that AI techniques are successfully applied to optimize and plan supply chains across various industries. The benefits are evident, including improvements in demand forecasting, inventory management, and overall planning. However, significant challenges remain, such as data quality issues, technical complexity, and organizational resistance. Addressing these barriers requires targeted solutions to enhance data quality, simplify technology integration, and manage organizational change effectively. Furthermore, organizations must prioritize explainability and interoperability to foster trust and seamless collaboration across multi-tier supply networks.

Future research should focus on exploring innovative AI applications and developing strategies to overcome these existing challenges. Overall, the review underscores AI’s transformative potential in supply chain optimization and highlights the need for continued innovation to improve efficiency and strategic decision-making.

Looking ahead, this study proposes the development of a Smart Decision-Making Framework for optimizing production parameters in complex industrial settings by leveraging Digital Twin technology. This framework will integrate real-time digital replicas of physical systems to enable continuous monitoring and optimization of production processes, such as cycle time, material usage, and energy consumption.

Leveraging AI and machine learning, the system will analyze data from sensors and production systems to predict optimal production parameters, reduce downtime, and maximize efficiency. It will also simulate various production scenarios and use optimization algorithms to suggest adjustments that minimize waste and enhance throughput. A real-time Decision Support System (DSS) will provide operators with actionable insights, enabling fast, data-driven decisions. Designed to be scalable across industries, this framework aims to serve sectors such as automotive, aerospace, pharmaceuticals, and energy where production optimization is critical to improving efficiency and reducing operational costs.

In conclusion, the integration of AI with emerging technologies like Digital Twins holds great promise for transforming supply chain and production planning. By combining advanced analytics, real-time monitoring, and decision support, future systems can drive both operational excellence and strategic agility in complex industrial environments.

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