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Functional Implementation of Artificial Intelligence in Supply Chains: A Review of Economic and Environmental Optimization

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Abstract:

Supply chain management is one of the most complex activities for companies. It faces several challenges, such as changing demand, disruptions, and environmental sustainability requirements. This complexity stems from the very nature of the supply chain, which encompasses a range of activities from raw material procurement and production to the distribution of finished products. The integration of advanced digital tools such as artificial intelligence is therefore imperative.

AI contributes to supply chain optimization by improving the coordination of flows and decision-making. However, existing studies focus on economic and operational gains, while the environmental impacts remain largely unexplored. This article aims to analyze the main functional applications of AI across all supply chain activities and highlights AI's contribution to the environmental optimization of the supply chain by improving the ecological footprint through optimized management of flows, resources, and various logistics processes. This research distinguishes itself from previous work by integrating the environmental dimension into the analysis of AI's role in supply chain optimization.

To achieve this objective, this study is based on a narrative literature review, which provides a critical synthesis of the existing literature and analyzes an aspect that has not yet been studied in depth: the impact of artificial intelligence on the environmental optimization of the supply chain. It is based on the analysis of 62 selected scientific articles published between 2020 and 2025 and sourced from high-quality scientific databases such as Scopus, Web of Science, and Science Direct, using keywords such as "supply chain," "artificial intelligence," and "optimization." The results show that AI improves economic optimizations such as cost reduction and improved operational efficiency, as well as environmental benefits such as reduced CO_2 emissions, energy consumption, and waste.

This study makes a dual contribution, both theoretical and managerial, by analyzing the contributions of artificial intelligence to the supply chain and providing a concise overview for companies to understand the opportunities and challenges of its adoption.

Keywords: Supply chain, Artificial intelligence, Economic optimization, Environmental optimization, Digital technologies.

Classification JEL : O33, M11

Paper type: Theoretical Research

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1. Introduction

In a context characterized by uncertainty, fierce international competition, and rapid technological change, supply chain performance depends on companies' ability to adapt to the digital age, where sustainability plays a central role. The application of artificial intelligence in supply chain management appears to be a strategic solution for achieving significant optimizations. (McCarthy, 1960), recognized as one of the first researchers to take an interest in artificial intelligence, defined it as the science and engineering of making intelligent machines, particularly intelligent computer programs. He considered it to be the art of making a machine do things that, when done by humans, require intelligence. Artificial intelligence is composed of several branches, including machine learning, deep learning, natural language processing (NLP), computer vision, robotics, and intelligent agents. For Ni et al (2020), artificial intelligence (AI) and machine learning (ML) tools based on algorithms that learn from experience are part of the fourth industrial revolution, in which machines are developed to adapt quickly to make decisions. The implementation of artificial intelligence in supply chains aims to improve product traceability, transform large amounts of data into useful information through learning and prediction algorithms, and increase operational efficiency (Aboussikine et al., 2023).

Several studies highlight that AI plays a crucial role in transforming supply chains into digital and sustainable supply chains, enabling cost optimization, faster response to customer needs, effective risk management, improved visibility, real-time decision-making, process automation, and reduced environmental impact (Dolgui & Ivanov, 2023). Beyond the economic adavantages, AI tools can optimize supply chains environmentally by reducing CO_2 emissions and resource waste (Shahzadi et al., 2024).

However, despite these benefits, the implementation of artificial intelligence faces many obstacles, including the very high cost of technology, resistance to change, lack of skills, and data quality.

Research confirms that AI plays an important role in enhancing supply chain performance, reducing cost and imporoving efficiency. On the other hand, previous studies mostly concentrate on the economic dimension by assessing the impact on performance and decision-making in a manner tied to environmental dimension and sustainability matters (Toorajipour et al., 2021) . Furthermore, there is a very limited number of studies that are comprehensive in explaining the impact of artificial intelligence on both dimensions, economic and environmental over the supply chain as a whole. This gap in the literature indicates a lack of comprehensive study and creates a need for further analysis on that subject.

This article aims to analyze in detail the influence of artificial intelligence on all supply chain activities, including procurement, storage, production, transportation, and distribution, as well as the optimizations possible at each stage of the logistics process thanks to AI. In this regard, this article aims to address the following issue: « ***To what extent does artificial intelligence optimize the various activities in the supply chain?*** ». This issue gives rise to the following two research questions:

- What are the main applications of AI in the supply chain?
- What are the obstacles to implementing AI?
- What are the main economic and environmental optimizations achieved through the use of artificial intelligence in the supply chain?

More specifically, this article presents, through a review of the narrative literature, a functional cartography of AI applications by logistics activity, their impact on economic and environmental optimization, and the main obstacles to their implementation. This article is organized into three sections. The first section presents the application of AI in supply chain activities. The second section analyzes the economic and environmental optimizations achieved through the implementation of AI. Finally, the third section discusses the main obstacles to the adoption of artificial intelligence in the supply chain. Through this analysis, our work contributes to a better understanding of how artificial intelligence can enhance the global performance of supply chains while supporting environmental sustainability.

2. Literature review

AI has become a key strategic lever for the digital transformation of the supply chain. Its application can be extended to the entire logistics cycle, from planification to final distribution, including production, control flow and supplier intersection. These technologies are integrated into advanced systems such as digital twins, smart factories, autonomous robots, and predictive analytics platforms, which form the foundations of Supply Chain 4.0 (Jahin et al., 2023).
An analysis of AI applications is essential to understanding their role within the various functions of the supply chain. To this end, the literature review is organized around the main functions of the supply chain namely, procurement, production, and transportation and logistics which are key drivers of the digital transformation of the modern supply chain. Each function is analyzed in terms of the major contributions of the literature as well as their main limitations.

2.1. Procurement

Procurement is the first step of the supply chain, where important decisions are made in term of supplier choice, cost control, input quality, conformity to standards, and flow continuity. In today's environments, characterized by uncertainty (economic, geopolitical, climatic) and high demand variability, AI has become an indispensable technical lever for managing complexity, increasing process agility, and ensuring better visibility of influential internal and external variables (Shahzadi et al., 2024). Existing studies show that the adoption of AI in procurement processes helps achieve economic optimisation by reducing procurement costs, streamlining timelines, and improving the quality of decisions, while also generating environmental benefits through the selection of responsible suppliers.
Here are the main technological applications of AI in procurement, along with the tools used and types of modeling.

Table 1: Applications of artificial intelligence in procurement

Forecast, Dynamic Adjustment of Requirements	• Predictive models and machine learning: Historical purchase data, seasonal factors, external market forecasts, and even meteorological data are fed into machine learning models to anticipate future purchase volumes. These models make it possible to calibrate orders according to variations in demand, which helps to plan supply more accurately and reduce the number of manual adjustments. • Demand sensing: This is a more reactive version of forecasting, where weak signals are detected in real time to adjust purchase forecasts. • Scenario simulation: To anticipate the rise or fall of certain risks (shortages, cost increases, supplier delays), AI tools combining simulation algorithms can be used to model several supply scenarios to determine the required stock levels, purchase schedule, or quotes to be issued.
Supplier Selection and Evaluation	• Analysis of structured and unstructured data: AI tools leverage various data sets, including supplier performance history, quality control results, delivery times, audits, financial data, and external data using SQL, text mining/NLP techniques, or open-source scraping to analyze potential risks. • Dynamic supplier segmentation: Using clustering or classification algorithms, suppliers can be grouped according to profiles (reliability, cost, capacity, location, risk level). • Supplier rating/scoring systems: AI can be used to assign numerical or weighted scores based on quantitative and qualitative criteria to compare suppliers.
Automation of Procurement Processes (Source-to-	• Intelligent S2P / P2P platforms: These platforms incorporate AI-based features to automate workflows: generating requests for quotes (RFQs), automatically matching relevant suppliers, analyzing bids, assisted negotiations, and automating the processing of purchase orders and invoices.

Pay / Procure-to-Pay)	• Generative artificial intelligence (GenAI): In some recent cases, platforms use generative models to draft or suggest contract clauses, analyze existing contracts for risks or inconsistencies, propose negotiations, or summarize complex terms for decision-makers.
Proactive Supplier Risk Detection	• Predictive risk models: By combining internal data (performance, deadlines) and external data (financial, geopolitical, climatic, regulatory), AI can anticipate disruptions, supplier failures, or potential disturbances. These models are based on techniques such as Random Forest, XGBoost… • Text analysis/NLP for compliance: Systems automatically analyze text, contracts, clauses, certifications, regulations, and media to detect regulatory changes, disputes, or weak signals of supplier dissatisfaction. • Real-time monitoring: By integrating continuous data streams, AI tools can automatically trigger alerts when certain risk thresholds are exceeded.

Source: (Ansari et al., 2020; Zoungrana, 2020)

From an economic perspective, these various applications make it possible to improve the accuracy of demand forecasts, reduce costs associated with planning errors, and enhance supply chain resilience. From an environmental perspective, they facilitate the integration of sustainability criteria into the supplier selection process, such as CO_2 emissions, energy footprint, and resource management practices, thereby contributing to a reduction in the overall environmental impact of the supply chain (Tseng et al., 2019).

However, these benefits are subject to several limitations, including reliance on high-quality data, technological integration constraints, and the complexity of information systems. In this regard, several studies have highlighted the challenges associated with integrating artificial intelligence into procurement processes.

Ivanov et al. (2019) and Kache & Seuring (2017) emphasize that the effectiveness of AI systems depends heavily on the availability and quality of data, as well as on companies' ability to integrate these technologies into complex information environments. Furthermore, other research has identified the main technical limitations associated with these applications. These limitations can be grouped into several categories:

- Data quality and integrity: The absence or poor structuring of historical data, supplier information, or performance feedback makes certain models unreliable.
- System interoperability: Intelligent purchasing platforms often need to integrate with other systems (ERP, financial systems, CRM systems), which poses technical challenges in terms of interface, standardization, and data synchronization.
- Complexity of processing unstructured data: NLP processing, while powerful, must overcome challenges related to language diversity, format variations, input errors, and biases in texts (e.g., non-standardized contracts).

AI in procurement manifests itself primarily through the implementation of predictive technologies, sophisticated analytics, process automation, and proactive monitoring tools. These applications go beyond technical modernization, they change how data is collected, structured, analyzed, and exploited, and alter the nature of decisions in the purchasing process, which become more focused on anticipation, compliance, and responsiveness. Thus, researchers confirm the central role of artificial intelligence in improving the optimization of procurement activities, both economically and environmentally. Nevertheless, these contributions remain dependent on specific technical and organizational conditions.

2.2. Production

The production function plays a significant role in the supply chain, as it links demand planning to manufacturing operations. In a context where companies are seeking to balance flexibility, traceability, and responsiveness in the face of uncertain markets, artificial intelligence is a major technological pillar of industrial transformation. It enables the use of data from machines, sensors, ERP and MES (Manufacturing Execution Systems) to support decision-making at various levels: strategic, tactical, and operational (Huang et al., 2021). AI is not a single technology, but a set of algorithmic models machine learning, computer vision, deep learning, natural language processing that interact to analyze, interpret, and predict the behavior of industrial processes. These models are now integrated into Industry 4.0 architectures, combining IoT (Internet of Things), cloud computing, digital twins, and cyber-physical systems (Dolgui & Ivanov, 2023). Several research highlight that integrating AI into production processes is a way to improve industrial performance. Huang et al. (2021) emphasize the role of AI in optimizing decision-making processes, while Dolgui & Ivanov (2023) stress its ability to enhance the resilience and adaptability of production systems in the face of disruptions. Production planning and scheduling are one of the historical fields of application for AI in industry. Optimization models based on machine learning and neural networks are used to manage complex systems where time, resources, and cost constraints must be balanced. Algorithms such as deep neural networks (DNN), genetic algorithms, and reinforcement learning methods now make it possible to continuously optimize the sequence of production tasks. For example, an AI system can adjust scheduling based on delays in raw material delivery, machine availability, or variations in demand, while respecting capacity and maintenance constraints (Wang et al., 2024). These applications help reduce operational costs, improve resource utilization rates, and shorten production lead times, while also contributing to environmental benefits by reducing energy consumption and resource waste through more efficient allocation of inputs (H. Zhang et al., 2022).

A second important contribution of AI in production concerns automated quality control. Thanks to computer vision systems coupled with deep learning models (CNN-Convolutional Neural Networks), companies can automatically identify visual anomalies on production lines like welding defects, scratches, assembly errors, deformations, etc. These systems operate at speeds and with greater precision than human inspection, while adapting to product variations. Cameras connected to AI models also enable continuous monitoring of the production process, detecting deviations in tolerances or abnormal equipment behavior (H. Zhang et al., 2022). In some cases, vision is combined with voice recognition or sound analysis (acoustic monitoring) to detect auditory anomalies in engines or machine tools. These combinations of multisensory signals illustrate AI's ability to simultaneously exploit multiple types of data to improve control accuracy (Raza, 2023). These systems help minimize costs associated with production defects and product returns; they also contribute to reducing scrap, industrial waste, and resource consumption linked to non-conforming production.

Another area where AI is applied is pedictive maintenance. Unlike preventive maintenance (based on fixed intervals), predictive maintenance relies on the real-time collection of data from sensors (vibration, temperature, pressure, electrical current) and its analysis by machine learning models. Algorithms such as random forests, LSTM (Long Short-Term Memory) networks, and autoencoders detect weak signals that indicate an imminent failure. This allows intervention only when necessary, avoiding unplanned production stoppages and extending the life of equipment (Huang et al., 2021). Digital twins play a fundamental role here. A digital twin is a virtual replica of a physical asset that integrates real-time data, simulating the behavior of the machine to predict failures and virtually evaluate different scenarios. AI also contributes to the optimization of industrial processes by automatically adjusting production parameters to maintain performance as close as possible to optimal conditions. Multi-objective optimization and reinforcement learning algorithms are used to adjust conveyor speed, temperature, pressure, or mixture composition based on actual conditions observed on production lines.

Modern production systems integrate IoT networks and AI-based traceability systems, enabling the entire life cycle of a product to be tracked, from the manufacturing station to packaging. These technologies use image recognition, data stream processing, and blockchain to ensure the consistency and integrity of information. AI also contributes to the management of internal

flows (WIP - Work In Progress), by locating and tracking semi-finished products in workshops via cameras, RFID sensors, or BLE beacons. This real-time traceability makes it possible to synchronize production with planning and avoid bottlenecks (Iung, 2019).
The studies analyzed show that artificial intelligence is a structural component of industrial management. In production, it enables the conversion of operational data into intelligent decisions, ensures continuity between planning, execution, and control, and equips industrial systems with self-learning capabilities. AI transforms production into a cognitive ecosystem, where machines, systems, and operators interact in a spirit of continuous improvement and adaptability. This evolution paves the way for autonomous and resilient production, which is one of the cornerstones of the supply chain.

2.3. Transportation and Logistics

Transportation and logistics are a central link in the supply chain, ensuring the efficient movement of raw materials and finished products. The complexity of flows, capacity constraints, and variability in delivery times require tools capable of processing large volumes of data and making quick decisions. Artificial Intelligence (AI) has become a major lever for managing these processes, combining machine learning, optimization, computer vision, and natural language processing (Bharadiya, 2023). The studies of Bharadiya, (2023) highlight the role of AI in last-mile management and the planning of delivery routes.

Table 2: Applications of AI in transportation and logistics

Route Optimization	AI algorithms, such as reinforcement learning and genetic algorithms, can generate optimized routes for transport fleets, considering traffic, delivery schedules, vehicle capacity, and external conditions (Konstantakopoulos et al., 2022).
Inventory and Warehouse Management	In warehouses, AI facilitates real-time inventory management and automation of operations. Predictive algorithms analyze product turnover and historical demand to adjust replenishment levels. Collaborative robots, coordinated by AI systems, perform picking and sorting with precision, reducing downtime and improving the flow of internal processes (Feizabadi, 2022).
Tracking and Traceability	AI integrated into IoT, GPS, and RFID systems enables continuous tracking of shipments and vehicles. Intelligent platforms, such as FourKites, leverage this data to detect delays or incidents and automatically adjust resource planning.
Risk Management	AI models detect anomalies in the logistics network and anticipate disruptions, whether related to transport delays, incidents, or congestion at logistics hubs (Ivanov, 2023).

Source: Authors

These applications have the potential to improve the performance of logistics systems, particularly through the optimization of flows, improved planning, and enhanced operational coordination. Several studies also link them to sustainability issues, although these have not always been the subject of in-depth research. Furthermore, some studies highlight the role of AI in the emergence of more adaptive and integrated logistics models, particularly in the context of urban logistics and last-mile delivery. However, these studies also underscore the existence of tensions between operational performance requirements and sustainability goals, particularly in environments characterized by constraints related to speed and flexibility. AI is transforming transportation and logistics into intelligent, adaptive processes capable of managing the complexity and variability of flows. Predictive systems, autonomous robotics, and tracking platforms ensure dynamic coordination of operations, laying the foundation for a responsive and flexible supply chain.
An analysis of the various applications of artificial intelligence in key supply chain activities underscores the role of AI technologies in transforming logistics systems. The studies reviewed show that AI has a positive impact on planning, coordination, and decision-making, enabling significant economic and environmental optimizations.

It therefore seems appropriate to analyze in greater depth the economic and environmental optimizations resulting from the adoption of AI in the supply chain, which is the subject of the following section.

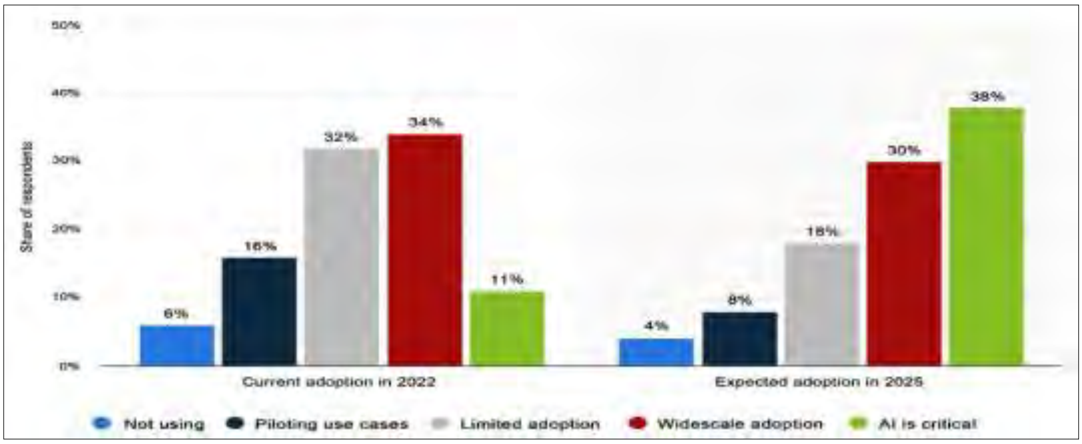
3. Economic and Environmental Optimizations through AI

The current environment is characterized by market volatility, complex supply chains, and gradually changing customer needs. Therefore, optimal supply chain management is important for companies seeking to improve their competitiveness and sustainability. Supply chain optimization is not limited to minimizing costs but also aims to balance quality, lead times, costs, flexibility, and reduced environmental impact (Ghoubach & El Amine, 2024). Traditional optimization methods that focus primarily on cost reduction have become insufficient. Companies should adopt a comprehensive approach that includes the various elements that impact supply chain performance, such as meeting deadlines, product or service quality, flexibility, agility, and advanced technological tools that can have a positive impact on operational efficiency and customer satisfaction. As a result, supply chains face the dual challenge of achieving economic optimization through cost reduction and environmental optimization through minimizing the negative effects of the supply chain on the environment.

The use of artificial intelligence technologies appears to be an effective solution. Artificial intelligence is perceived by Frimousse & Peretti (2024) as "*a revolution within a revolution: an algorithmic revolution within a digital revolution.*" Artificial intelligence can be used by managers in various activities throughout the supply chain, such as demand planning, purchasing, inventory management, production, risk management, transportation, and distribution. Zhang et al. (2023) studied the impact of e-commerce development on the increase in the volume of goods. The study mentions that in 2018, the express delivery sector in China achieved 50.5 billion units, which prompted several companies in the logistics sector to use artificial intelligence to improve efficiency and optimize logistics flow management.

AI is applied in the logistics chain to improve performance from a Lean and Agile perspective. Several companies are investing in digital solutions to optimize their supply chain operations. Figure (1) illustrates the global adoption rate of artificial intelligence in the supply chains of industrial companies (Mohsen, 2023). The literature indicates that AI enhances companies' ability to respond to changes in demand, eliminate waste, and improve collaboration and consumer satisfaction.

Figure 1: Global AI adoption rate in supply chain and manufacturing businesses (2022 and 2025)



Source: Statista (2022).

AI can therefore change the way the supply chain operates and optimize routes, forecasting, fleet management, and real-time delivery tracking (Ousmane et al., 2023). Artificial intelligence offers both economic and environmental benefits, enabling a higher level of competitiveness to

be achieved. The impact of AI on the supply chain can be analyzed from two perspectives. From an economic perspective, which concerns costs, productivity, and the resilience of the supply chain. From an environmental perspective, which relates to CO_2 emissions, resource consumption, and waste generation. However, these two dimensions are not always compatible, raising the question of trade-offs between economic and environmental optimizations.
The following presents an analysis of recent scientific literature on supply chain optimizations and environmental improvements that can be achieved through artificial intelligence.

3.1. Economic Optimizations

Artificial intelligence plays a crucial role in strengthening the supply chain. One of the main advantages of using AI in logistics management is cost reduction. From this perspective, the economic optimization delivered by AI relies on several mechanisms that enable measurable gains in logistics costs, productivity, and service levels.
Improved forecasting is a key driver of economic optimization. A 2022 McKinsey survey shows that AI makes it possible to leverage real-time data, refine production and inventory approaches, and make accurate demand forecasts, leading to lower costs and more economical logistics practices. Companies that have adopted AI in their supply chains have seen a 15% reduction in logistics costs, a 35% increase in inventory efficiency, and a 65% improvement in service levels. Seventy percent of managers at more than 150 companies report a significant return on investment from artificial intelligence (Cohen & Tang, 2024). Similarly, Balouza (2024) confirms through the results of an empirical study that the application of artificial intelligence to production planning increases the efficiency of supply chain management. Mohsen (2023) also reported that the integration of prediction algorithms enables better resource management and reduces transportation and inventory costs. These results demonstrate that improved forecasting helps reduce operational uncertainties, optimize resource allocation, and improve the service rate, which is a key economic performance indicator. Another key mechanism involves optimizing inventory levels using the analytical capabilities of AI. Artificial intelligence performs precise calculations and machine learning, as well as analyzing historical trends and creating prediction models based on the results, which improves real-time inventory management. AI systems simplify route planning, schedule consumer requests, and adjust inventory levels as needed. This helps control inventory management by avoiding the costs associated with overstocking and stockouts. This optimization helps improve inventory turnover, reduce storage costs, and minimize losses from excess inventory, thereby enhancing the overall profitability of logistics operations (Vakulabharanam, 2020).
Furthermore, optimizing logistics operations and transport routes is a key driver of productivity improvement. AI helps efficiently manage warehouses, deliveries, and collection points to ensure timely delivery to customers (Ousmane et al., 2023). Artificial intelligence ensures product availability by monitoring and adjusting inventory levels, and its integration into virtual assistants across various industries promotes increased productivity and collaboration (Ajami & Karimi, 2023). The use of optimization algorithms helps reduce travel distances, improve resource utilization, and lower transportation costs, resulting in a significant improvement in operational productivity (Gülen, 2023).
AI also improves visibility by providing detailed mapping of the supply chain, helping to avoid risks and disruptions that supply chains may encounter. AI monitors market demand and changes in supply by analyzing all data to prevent disruptions, enabling companies to develop preventive strategies to proactively strengthen supply chain resilience (Balouza, 2024). This increased visibility helps reduce the costs associated with disruptions and improves operational continuity, thereby contributing to better economic performance (Dolgui & Ivanov, 2023).
Furthermore, predictive maintenance serves as an additional mechanism for cost optimization made possible by artificial intelligence. By analyzing data from sensors, AI systems can identify

early warning signs of failure and schedule maintenance before major breakdowns occur. This mechanism reduces corrective maintenance costs, minimizes unplanned downtime, and improves equipment availability, thereby boosting productivity and reducing financial losses (Zdolsek Draksler et al., 2023).
The intelligent automation of logistics processes is another key mechanism contributing to economic optimization. The integration of AI-based tools enables the automation of tasks such as order management, data processing, and the coordination of information flows. Automation reduces human error, speeds up operations, and lowers administrative and operational costs, thereby improving supply chain efficiency (Ali et al., 2025).
The following table summarizes the benefits derived from the application of artificial intelligence in supply chain management:

Table 3: Summary of the advantages of AI in the supply chain

Benefits	**Reference**
"The integration of AI provides companies with an autonomous supply chain that can transform into a conscious, self-managed, and self-defining system."	(Stoyanov, 2021)
"Real-time monitoring and control of AI-enabled production and logistics processes can lead to increased responsiveness and flexibility in supply chain management. This can help companies adapt quickly to changes in demand and other disruptions, leading to improved performance."	McKinsey & Company (2021)
"AI can improve transparency in supply chain management by providing real-time visibility into logistics and production processes. This can help companies identify and respond to issues more quickly, reducing waste and increasing efficiency."	(Gülen, 2023)
"AI can improve collaboration between different stakeholders in the supply chain, such as suppliers, manufacturers, and retailers. By facilitating communication and information sharing, AI can help companies work together more effectively, leading to better performance. "	(Mohsen, 2023)

Source: Authors

In summary, studies show that artificial intelligence improves the economic efficiency of the supply chain by lowering costs, improving productivity, strengthening resilience, and generating significant returns. However, widespread adoption requires overcoming structural barriers and ensuring responsible use of the technology.

3.2. Environmental Optimizations

Given the economic and ecological crises that have affected the entire world, companies increasingly need a sustainable and responsible supply chain. The implementation of a green supply chain seems to be the effective solution for a more environmentally friendly future (Frimousse & Peretti, 2024). Artificial intelligence technologies facilitate the transformation of the supply chain into a digitalized and sustainable supply chain capable of responding to both economic and environmental constraints. In addition to its role in improving operational efficiency, AI contributes to the environmental sustainability of all supply chain activities, including procurement, production, transportation (by optimizing routes to minimize the carbon footprint), warehousing, distribution, and reverse logistics (Ousmane et al., 2023).
In upstream supply chain activities, particularly in procurement, AI enables firms to assess suppliers' environmental performance, select more sustainable partners, and incorporate environmental criteria into their sourcing processes (Govindan et al., 2022).Pant & Palanisamy (2025) expand on this idea by pointing out that artificial intelligence enhances traceability and environmental transparency by improving supply chain visibility through monitoring suppliers' environmental activities and regulatory compliance. Lin et al. (2025) add that artificial intelligence facilitates carbon footprint tracking and the assessment of sustainable practices at all links in the supply chain. In terms of production processes, AI helps optimize energy consumption through predictive maintenance systems and intelligent control of industrial

operations (H. Zhang et al., 2022). AI also contributes to the eco-design of products by enabling the simulation of various design scenarios that incorporate environmental criteria, thereby helping to reduce the environmental impact throughout the entire product lifecycle (Bocken et al., 2016).

In warehousing operations, AI helps optimize the management of internal flows, reduce unnecessary movement, and improve warehouse energy efficiency, particularly through automation and the use of advanced energy management systems (Perotti et al., 2025).

Furthermore, AI helps improve vehicle load factors, synchronize logistics operations, and reduce empty runs, thereby helping to mitigate the environmental impact of transportation activities (Ivanov, 2023). Artificial intelligence, as mentioned by Sanz et al. (2018) enables the design of optimal routes, which has a positive effect on the environment, particularly in terms of reducing CO2 emissions and saving fuel costs. American companies are adopting green logistics practices that also aim to reduce delivery frequency, optimize fleet utilization, and adopt energy-efficient technologies. In the US, companies are increasingly using AI-based predictive analytics to consolidate flows, thereby reducing unnecessary transportation and significantly lowering carbon emissions (Cohen & Tang, 2024). In the distribution sector, AI also promotes the development of more sustainable logistics models, such as collaborative delivery, the consolidation of shipments, and the use of low-emission alternative modes of transport (Sharma et al., 2021).

Finally, AI plays an important role in reverse logistics management by facilitating the collection, sorting, and recovery of end-of-life products. It thereby helps improve recycling, reuse, and remanufacturing rates, actively contributing to the development of circular economy models (Akkermans et al., 2024). Bibliometric analysis conducted by Noman et al. (2022) reveals that artificial intelligence simplifies waste sorting and recycling, which improves circular models in the supply chain. Similarly, Li et al. (2020) confirm that integrating artificial intelligence algorithms into production planning helps reduce industrial waste and use resources efficiently.

Research to date agrees on the crucial role that artificial intelligence plays in building more sustainable supply chains, although the challenge remains of balancing the environmental benefits with the energy costs associated with its implementation. Overall, AI has become a key driver of efficiency, sustainability, and innovation in the supply chain, offering numerous benefits to businesses while helping to reduce the environmental impact of supply chain operations.

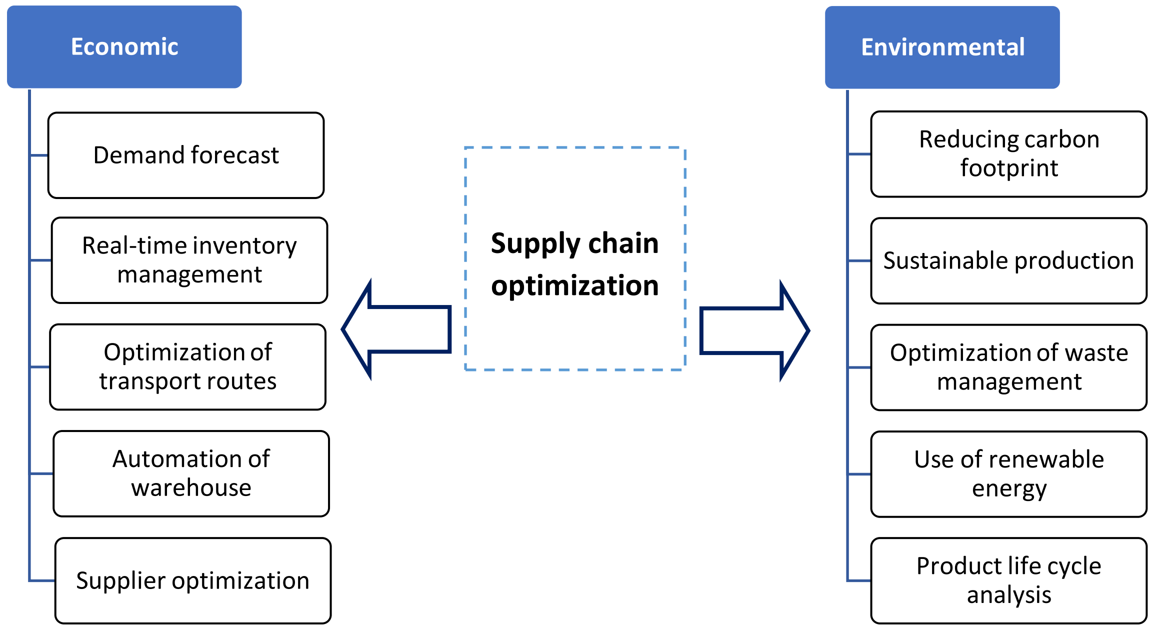
However, achieving these environmental optimizations depends on a number of conditions. First, the quality, availability, and integration of data are essential prerequisites, as incomplete or biased data can lead to environmentally ineffective decisions (Jarrahi, 2018). Second, the energy mix of digital infrastructure plays a decisive role; the use of data centers powered by fossil fuels can significantly reduce, or even negate, the environmental gains generated by operational optimization (Balouza, 2024). Furthermore, the governance of AI systems appears to be a key success factor, involving the establishment of organizational and regulatory frameworks to ensure transparency, traceability, and alignment of AI systems with sustainability objectives (Chaudhuri et al., 2024).

Furthermore, other factors also determine whether these benefits are actually realized, such as companies' level of digital maturity, employees' skills, and the feasibility of integrating AI tools into existing decision-making processes (Kache & Seuring, 2017). Data security, customer privacy, and regulatory issues also require special attention to ensure the successful integration of artificial intelligence into the supply chain.

Analysis of existing research shows that the implementation of artificial intelligence in the supply chain has a dual impact, both environmentally and economically. It enables significant optimizations, contributing positively to improving business performance and productivity.

The figure below illustrates the main economic and environmental optimizations achieved through the integration of artificial intelligence into the supply chain.

Figure 2: Supply Chain Optimization



Source: Authors

From this perspective, the relationship between economic and environmental optimization appears to be synergistic, insofar as many AI tools make it possible to reduce both operational costs and the environmental footprint, particularly through the optimization of physical flows, resource optimization, and support for the circular economy. This “win-win” approach demonstrates that technological innovation is a driver of sustainability. However, this relationship is not always aligned and may lead to trade-offs, particularly in the short term. Indeed, the implementation of AI technologies often involves high initial investments related to digital infrastructure, skills, and system integration, which can act as a barrier for some companies (Kache & Seuring, 2017). Furthermore, the energy consumption of data centers and AI systems can generate a significant carbon footprint, which may partially offset the environmental gains achieved at the operational level (Balouza, 2024).

Thus, achieving economic and environmental optimizations depends on companies’ ability to effectively balance these two dimensions by adopting a long-term vision and integrating environmental criteria into their technology investment decisions. From this point of view, AI is not merely a tool for optimization, but also a strategic lever that requires appropriate governance to balance economic and environmental performance.

4. Barriers to AI Adoption in Supply Chain Management

The barriers to AI adoption in SCM are multidimensional, evolving, and deeply interconnected, shaped by both the dynamic technological landscape and the broader sociotechnical environment in which supply chains operate. This These obstacles can be divided into three categories : technological barriers, organizational and human barriers, and contextual and regulatory barriers each systematically examined through general empirical findings, sector-specific illustrations (e.g., SMEs, humanitarian supply chains, port logistics), and actionable overcoming strategies. This tripartite structure, informed by systematic reviews and empirical studies published between 2022 and 2025, aims to enhance both the readability and the analytical coherence of the analysis (Bag et al., 2021; Modgil et al., 2022).

Beyond cataloguing persistent challenges, this analysis simultaneously identifies emerging pathways for responsible and scalable AI adoption. By explicitly accounting for disparities in digital maturity from multinational corporations to resource-constrained SMEs and humanitarian actors it underscores the necessity of adaptive, context-sensitive frameworks that condition both the pace and the scope of AI integration in supply chain ecosystems.

4.1. Technological Barriers

Technological barriers constitute a primary and multifaceted impediment to AI adoption in Supply Chain Management (SCM). They encompass challenges related to digital infrastructure, complex algorithms, and the tools required to deploy advanced systems such as machine learning (ML), predictive analytics, and digital twins. A systematic review indexed in *Scopus* highlights data quality and availability as central issues: fragmented, biased, or incomplete datasets compromise the reliability and accuracy of AI models, leading to predictive errors and heightened operational risks, with estimated efficiency losses ranging between 15% and 30% in global supply chains (Bag et al., 2021). For instance, in humanitarian supply chains analyzed by Anene & Clement (2022), the integration of predictive analytics is hindered by fragile infrastructure in volatile environments, where IoT sensors often operating in hybrid configurations with AI suffer from connectivity interruptions, thereby reducing end-to-end visibility by 20–40%, according to empirical simulations. A recent empirical study on small and medium-sized enterprises (SMEs) corroborates these findings, identifying cloud system scalability as a major constraint for big data processing. High computational costs limit access to advanced technologies, reinforcing digital maturity disparities across organizations (Schlegel et al., 2023; Daios et al., 2025).

Another critical and recurring barrier is system interoperability. AI solutions must integrate seamlessly with legacy platforms such as ERP, TMS, and WMS; however, heterogeneous protocols and disparate standards create persistent data silos. A Web of Science survey of 300 SCM managers reports that 45% of respondents identify incompatibility as the main technological bottleneck. Further extend this analysis to AI–blockchain hybrid architectures, where scalability challenges particularly real-time data processing of massive volumes hamper adoption, resulting in latency increases of 15–30% in industrial cases and a growing dependence on complex middleware solutions (Culot et al., 2024). In addition, cybersecurity and data privacy vulnerabilities remain major concerns, with studies reporting a 20% rise in cyber incidents within digitalized supply chains. Empirical evidence further quantifies initial implementation cost increases of 20–50%, rendering AI adoption prohibitive for resource-constrained firms (Hangl et al., 2022; Modgil et al., 2022).

To overcome these technological obstacles, four strategies have been empirically validated. First, the adoption of low-code/no-code AI platforms lowers the technical entry barrier for organizations with limited IT expertise. Second, strategic cloud partnerships (e.g., AWS, Azure) provide scalable, cost-efficient infrastructure, particularly for SMEs. Third, the standardization of interoperability protocols (e.g., API-first architectures) facilitates seamless integration of AI with legacy ERP and TMS systems. Fourth, federated learning and differential privacy frameworks simultaneously address cybersecurity and data sovereignty concerns. Longitudinal case studies confirm that such modular approaches can reduce integration costs by 25–35% while improving interoperability outcomes (Hangl et al., 2022). Collectively, technological readiness, interoperability maturity, and cybersecurity governance constitute the foundational prerequisites for the sustainable and large-scale deployment of AI in supply chain ecosystems.

4.2. Organizational Barriers

Organizational barriers stem from the internal dynamics of firms, encompassing resistance to change, deficits in specialized competencies, and a lack of strategic managerial support. A qualitative study indexed in *Scopus* focusing on Moroccan and European firms identifies the perceived complexity of AI as a dominant inhibitor, where fear of automation and insufficient training generate human resistance, reducing adoption rates by 40–50% in hierarchical organizations (Najari et al., 2025). This aligns with Treiblmaier (2018), who examined decentralization challenges in SCM: implementing AI necessitates a redistribution of decision-making processes, yet rigid organizational cultures and deliberative managerial attitudes hinder this transformation (Hangl et al., 2022). A shortage of specialized AI expertise emerges as another critical challenge. Reviews indexed in *Web of Science* highlight significant gaps in data scientists, machine learning engineers, and qualified SCM professionals, a deficiency particularly acute in SMEs where budgetary constraints limit recruitment and training (Cadden et al., 2022). Furthermore, high investments in software, hardware, and workforce development discourage smaller entities. In humanitarian supply chains, NGOs struggle to fund AI initiatives despite their resilience benefits, resulting in project failure rates exceeding 35% (Anene & Clement, 2022; Culot et al., 2024). Without strategic commitment from top management, AI initiatives are prone to failure, with adoption rates falling below 30% in organizations lacking a clear ROI vision (Verma et al., 2022).

To address these barriers effectively, three categories of interventions have proven most effective. At the individual level, hybrid training programs combining e-learning, on-the-job coaching, and AI literacy workshops reduce resistance and build internal competencies. At the structural level, academia–industry partnerships and dedicated AI Centers of Excellence facilitate access to specialized talent while aligning AI projects with strategic objectives. At the managerial level, the systematic development of phased implementation roadmaps and total-cost-of-ownership (TCO) frameworks strengthens executive commitment and secures long-term organizational buy-in. Empirical evidence confirms that these combined interventions can increase AI adoption rates by 20–40%, fostering a culture of organizational learning conducive to sustainable digital transformation (Modgil et al., 2022; Cadden et al., 2022).

4.3. Contextual Barriers

Contextual barriers encompass exogenous factors such as regulatory frameworks, ethical concerns, and inter-organizational dynamics that shape AI adoption at the macro level. Ethical issues - including algorithmic biases that may perpetuate discrimination in supplier selection or resource allocation - constitute a major deterrent, particularly within cross-border supply chains where heightened transparency is required (Dubey et al., 2019). El Imrani (2016) illustrates these constraints through the case of Tangier Med Port, where regulatory barriers complicate the integration of predictive AI systems. Recent systematic reviews underscore how AI biases exacerbate inequalities in healthcare and humanitarian supply chains, leading to adoption delays of 2–3 years in vulnerable contexts (Mir et al., 2020).

Moreover, multi-actor collaboration poses substantial challenges. In SCM, AI deployment relies on multi-party data sharing, yet reluctance persists due to competitive concerns, disparate standards, and cybersecurity issues. This is particularly evident in humanitarian supply chains, where divergences between local and international actors hinder coordination (Khan et al., 2021). Data privacy regulations (e.g., GDPR, CCPA) impose additional compliance constraints, increasing costs by 10–25% (Ozdemir et al., 2021). Meta-analyses indicate that contextual barriers can delay AI adoption by 2–5 years in emerging economies, emphasizing the urgency of regulatory harmonization (Mir et al., 2020).

To address these contextual barriers, multi-level governance strategies are required. At the international level, harmonization of regulatory frameworks particularly regarding data privacy and AI transparency is essential to reduce compliance fragmentation across supply chain actors. At the sectoral level, the development of industry-specific ethical AI charters and systematic algorithmic bias audits can restore stakeholder trust. At the inter-organizational level, the establishment of trusted data-sharing consortia, supported by blockchain-based governance models, offers a viable pathway to collaborative AI deployment. In emerging markets particularly in North Africa and Sub-Saharan Africa targeted capacity-building programs are critical to bridging the digital divide (Cannas et al., 2024; Mir et al., 2020).

It is important to underscore that the barriers identified in this section directly condition the realizability of the economic and environmental optimizations analyzed in Section 3. Data quality deficits and interoperability gaps compromise the accuracy of demand forecasting models and predictive maintenance systems, thereby eroding the efficiency gains documented earlier including the 15–30% cost reductions and 10–20% CO_2 emission savings attributed to AI-driven logistics. Organizational resistance and competency gaps further limit firms' ability to deploy route optimization or carbon footprint monitoring tools at scale. Regulatory and ethical barriers, particularly in cross-border contexts, constrain the traceability applications that form a central pillar of AI's contribution to sustainable logistics. Consequently, the full economic and environmental potential of AI in SCM remains conditional on a holistic resolution of these interconnected obstacles, reinforcing the case for integrated, multi-dimensional adoption frameworks (Bag et al., 2021; Hangl et al., 2022).

5. Conclusion

This article set out to analyze the functional applications of artificial intelligence across the main activities of supply chain management procurement, production, transportation, inventory management, and traceability and to assess AI's dual contribution to economic and environmental optimization. Drawing on a narrative literature review of 62 peer-reviewed articles published between 2020 and 2025 and sourced from Scopus, Web of Science, and Science Direct, this study provides a critical synthesis of existing knowledge while specifically addressing a dimension that remains underexplored: the impact of AI on the environmental performance of supply chains. This integrative perspective, combining functional cartography with a systematic articulation of economic and environmental outcomes, constitutes the article's primary contribution relative to prior reviews.

Three major findings emerge from this review. First, AI generates significant economic optimizations across all supply chain functions: demand forecasting models reduce inventory costs by 20–30%, predictive maintenance systems cut unplanned downtime by up to 40%, and route optimization algorithms lower transportation expenditures by 15–25%. Second, and more distinctively, this study demonstrates that AI contributes substantively to environmental performance: optimized routing reduces CO_2 emissions by 10–20%, AI-driven energy management systems lower industrial energy consumption by 15–30%, and machine learning applications in circular economy logistics support waste reduction and material recovery at scale. Third, the analysis reveals that these benefits remain conditional on overcoming a structured set of technological, organizational, and contextual barriers and that these barriers directly condition the realization of the optimizations documented in this review. From a theoretical standpoint, this article distinguishes itself from prior work by offering an integrated, function-by-function cartography that systematically articulates economic and environmental dimensions within a unified analytical framework.

From a managerial perspective, this study provides practitioners with an actionable roadmap: organizations are encouraged to prioritize phased integration strategies, invest in AI literacy and change management programs, and develop robust ROI frameworks before committing to large-scale deployments. Supply chain managers in emerging markets particularly in North

Africa should additionally engage with policymakers to advocate for harmonized regulatory frameworks that reduce compliance costs and foster cross-border data sharing. From a research perspective, several avenues remain open: future empirical studies should quantify economic–environmental trade-offs of AI adoption across specific industry sectors; longitudinal analyses are needed to assess the durability of AI-generated optimizations under volatile geopolitical conditions; and multi-country comparative studies could illuminate how institutional and cultural factors moderate AI adoption dynamics. The investigation of AI integration in under-researched logistics ecosystems such as those in North Africa represents a particularly promising and policy-relevant frontier for future research.

References

(1). Aboussikine, H., Bendimerad, S., Sauvage, T., & Haouari, M. (2023). Comment l'Intelligence Artificielle dompte la traçabilité des processus Supply Chain? Application à NOZ France. *CIGI QUALITA MOSIM 2023*. https://cnam.hal.science/hal-04536092/

(2). Ajami, R. A., & Karimi, H. A. (2023). Artificial Intelligence : Opportunities and Challenges. *Journal of Asia-Pacific Business*, *24*(2), 73-75. https://doi.org/10.1080/10599231.2023.2210239

(3). Akkermans, H., Basten, R., Zhu, Q., & Van Wassenhove, L. (2024). Transition paths for condition-based maintenance-driven smart services. *JOURNAL OF OPERATIONS MANAGEMENT*, *70*(4), 548-567. (WOS:001153487200001). https://doi.org/10.1002/joom.1295

(4). Ali, A. A., Abu Hussein, A., Al-Jaghoub, S., Alheet, A. F., & Attiany, M. (2025). The Impact of Digital Technology, Automation, and Data Integration on Supply Chain Performance : Exploring the Moderating Role of Digital Transformation. *Logistics*, *9*(1). Scopus. https://doi.org/10.3390/logistics9010011

(5). Anene, U. N., & Clement, T. (2022). A resilient logistics framework for humanitarian supply chains : Integrating predictive analytics, IoT, and localized distribution to strengthen emergency response systems. *International Journal of Scientific Research in Computer Science, Engineering and Information Technology*, *8*(5), 398-424.

(6). Ansari, F., Glawar, R., & Sihn, W. (2020). Prescriptive Maintenance of CPPS by Integrating Multimodal Data with Dynamic Bayesian Networks. In J. Beyerer, A. Maier, & O. Niggemann (Éds.), *Machine Learning for Cyber Physical Systems* (Vol. 11, p. 1-8). Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-662-59084-3_1

(7). Bag, S., Gupta, S., Kumar, S., & Sivarajah, U. (2021). Role of technological dimensions of green supply chain management practices on firm performance. *JOURNAL OF ENTERPRISE INFORMATION MANAGEMENT*, *34*(1), 1-27. https://doi.org/10.1108/JEIM-10-2019-0324

(8). Balouza, M. (s. d.). Evaluating the Economic Impacts of Artificial Intelligence Integration on Supply Chain Management; a Mediation Analysis Through Ai Capability. *Available at SSRN 4811492*. Consulté 3 octobre 2025, à l'adresse https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4811492

(9). Bharadiya, J. P. (2023). Artificial intelligence in transportation systems a critical review. *American Journal of Computing and Engineering*, *6*(1), 35-45.

(10). Bocken, N. M. P., De Pauw, I., Bakker, C., & Van Der Grinten, B. (2016). Product design and business model strategies for a circular economy. *Journal of Industrial and Production Engineering*, *33*(5), 308-320. https://doi.org/10.1080/21681015.2016.1172124

(11). Cadden, T., Dennehy, D., Mantymaki, M., & Treacy, R. (2022). Understanding the influential and mediating role of cultural enablers of AI integration to supply chain.

International Journal of Production Research, *60*(14), 4592-4620. https://doi.org/10.1080/00207543.2021.1946614
(12). Cannas, V. G., Ciano, M. P., Saltalamacchia, M., & Secchi, R. (2024). Artificial intelligence in supply chain and operations management : A multiple case study research. *International Journal of Production Research*, *62*(9), 3333-3360. https://doi.org/10.1080/00207543.2023.2232050
(13). Chaudhuri, R., Chatterjee, S., Mariani, M., & Wamba, S. (2024). Assessing the influence of emerging technologies on organizational data driven culture and innovation capabilities : A sustainability performance perspective. *TECHNOLOGICAL FORECASTING AND SOCIAL CHANGE*, *200*. (WOS:001150914500001). https://doi.org/10.1016/j.techfore.2023.123165
(14). Cohen, M., & Tang, C. (2024). The role of AI in developing resilient supply chains. *Georgetown Journal of International Affairs*.
(15). Culot, G., Podrecca, M., & Nassimbeni, G. (2024). Artificial intelligence in supply chain management : A systematic literature review of empirical studies and research directions. *Computers in industry*, *162*, 104132.
(16). Daios, A., Kladovasilakis, N., Kelemis, A., & Kostavelis, I. (2025). AI applications in supply chain management : A survey. *Applied Sciences*, *15*(5), 2775.
(17). Dolgui, A., & Ivanov, D. (2023). Metaverse supply chain and operations management. *International Journal of Production Research*, *61*(23), 8179-8191. https://doi.org/10.1080/00207543.2023.2240900
(18). Dubey, R., Gunasekaran, A., & Childe, S. J. (2019). Big data analytics capability in supply chain agility : The moderating effect of organizational flexibility. *Management decision*, *57*(8), 2092-2112.
(19). EL IMRANI, O. (2016). The logistics of port container terminals : What prospects for fostering the role of Tangier Med port in the global maritime logistics? *Revue d'Economie et de Gestion JBE*. https://www.academia.edu/download/58362589/Article_05.pdf
(20). Feizabadi, J. (2022). Machine learning demand forecasting and supply chain performance. *International Journal of Logistics Research and Applications*, *25*(2), 119-142. https://doi.org/10.1080/13675567.2020.1803246
(21). Frimousse, S., & Peretti, J.-M. (2024). Regards croisés:«Quelle organisation demain pour fidéliser les collaborateurs?». *Question (s) de management*, *48*(1), 143-228.
(22). GHOUBACH, S., & EL AMINE, B. (2024). Le rôle de l'optimisation des coûts logistiques à l'amélioration de l'efficacité des opérations de la chaîne d'approvisionnement. *International Journal of Accounting Finance Auditing Management and Economics*, *5*(4), 567-582.
(23). Govindan, K., Kannan, D., Jørgensen, T. B., & Nielsen, T. S. (2022). Supply Chain 4.0 performance measurement : A systematic literature review, framework development, and empirical evidence. *Transportation Research Part E: Logistics and Transportation Review*, *164*. Scopus. https://doi.org/10.1016/j.tre.2022.102725
(24). Gülen, K. (2023). Unleashing the power of AI with the rise of intelligent supply chain management. *Artificial Intelligence, Industry, Transportation & Logistics. https://dataconomy. com/2023/01/artificial-intelligence-supply-chain*.
(25). Hangl, J., Behrens, V. J., & Krause, S. (2022). Barriers, drivers, and social considerations for AI adoption in supply chain management : A tertiary study. *Logistics*, *6*(3), 63.
(26). Huang, Z., Shen, Y., Li, J., Fey, M., & Brecher, C. (2021). A survey on AI-driven digital twins in industry 4.0 : Smart manufacturing and advanced robotics. *Sensors*, *21*(19), 6340.

(27). Iung, B. (2019). De la maintenance prédictive à la maintenance prescriptive : Une évolution nécessaire pour l'industrie du futur. *Conference on Complexity Analysis of Industrial Systems and Advanced Modeling, CAISAM 2019*. https://hal.science/hal-02126720/

(28). Ivanov, D. (2023). The Industry 5.0 framework : Viability-based integration of the resilience, sustainability, and human-centricity perspectives. *International Journal of Production Research*, *61*(5), 1683-1695. Scopus. https://doi.org/10.1080/00207543.2022.2118892

(29). Ivanov, D., Dolgui, A., & Sokolov, B. (2019). The impact of digital technology and Industry 4.0 on the ripple effect and supply chain risk analytics. *International Journal of Production Research*, *57*(3), 829-846. https://doi.org/10.1080/00207543.2018.1488086

(30). Jahin, M. A., Naife, S. A., Saha, A. K., & Mridha, M. F. (2023). Ai in supply chain risk assessment : A systematic literature review and bibliometric analysis. *arXiv preprint arXiv:2401.10895*. https://www.researchgate.net/profile/Md-Abrar-Jahin-2/publication/377628539_AI_in_Supply_Chain_Risk_Assessment_A_Systematic_Literature_Review_and_Bibliometric_Analysis/links/67c56583461fb56424eef7e9/AI-in-Supply-Chain-Risk-Assessment-A-Systematic-Literature-Review-and-Bibliometric-Analysis.pdf

(31). Jarrahi, M. H. (2018). Artificial intelligence and the future of work : Human-AI symbiosis in organizational decision making. *Business horizons*, *61*(4), 577-586.

(32). Kache, F., & Seuring, S. (2017). Challenges and opportunities of digital information at the intersection of Big Data Analytics and supply chain management. *International journal of operations & production management*, *37*(1), 10-36.

(33). Khan, M., Imtiaz, S., Parvaiz, G. S., Hussain, A., & Bae, J. (2021). Integration of internet-of-things with blockchain technology to enhance humanitarian logistics performance. *IEEE Access*, *9*, 25422-25436.

(34). Konstantakopoulos, G. D., Gayialis, S. P., & Kechagias, E. P. (2022). Vehicle routing problem and related algorithms for logistics distribution : A literature review and classification. *Operational research*, *22*(3), 2033-2062.

(35). Li, X., Cao, J., Liu, Z., & Luo, X. (2020). Sustainable business model based on digital twin platform network : The inspiration from haier's case study in China. *Sustainability*, *12*(3), 936.

(36). Lin, Y., Pang, G., Duan, K., Luo, J., Wang, S., & Qu, J. (2025). The impacts of digital and learning orientations on supply chain resilience. *Industrial Management and Data Systems*, *125*(2), 535-574. Scopus. https://doi.org/10.1108/IMDS-04-2024-0379

(37). McCarthy, J. (1960). *Programs with common sense*. RLE and MIT computation center Cambridge, MA, USA. http://www.cs.rit.edu/~rlaz/is2014/files/McCarthyProgramsWithCommonSense.pdf

(38). Mir, U. B., Sharma, S., Kar, A. K., & Gupta, M. P. (2020). Critical success factors for integrating artificial intelligence and robotics. *Digital Policy, Regulation and Governance*, *22*(4), 307-331.

(39). Modgil, S., Singh, R. K., & Hannibal, C. (2022). Artificial intelligence for supply chain resilience : Learning from Covid-19. *The international journal of logistics management*, *33*(4), 1246-1268.

(40). Mohsen, B. M. (2023). Impact of artificial intelligence on supply chain management performance. *Journal of Service Science and Management*, *16*(1), 44-58.

(41). Najari, O., Ayi, O., & Cheklekbire, M. (2025). Resistance to Change and Implementation Challenges of AI in Moroccan Public Administrations. *International Journal of Research in Economics and Finance*, *2*(5), 44-53.

(42). Ni, D., Xiao, Z., & Lim, M. K. (2020). A systematic review of the research trends of machine learning in supply chain management. *International Journal of Machine Learning and Cybernetics, 11*(7), 1463-1482. https://doi.org/10.1007/s13042-019-01050-0

(43). Noman, A. A., Akter, U. H., Pranto, T. H., & Haque, A. K. M. (2022). Machine learning and artificial intelligence in circular economy : A bibliometric analysis and systematic literature review. *Annals of Emerging Technologies in Computing (AETiC)*, *6*(2), 13-40.

(44). Ousmane, K., Aziz, E. K., & Hicham, E. A. (2023). REVOLUTION LOGISTIQUE : L'INTELLIGENCE ARTIFICIELLE TRANSFORME LE DERNIER KILOMETRE. *Revue Marocaine de Management, Logistique et Transport*, (6). https://revues.imist.ma/index.php/RMLT/article/download/48292/25337

(45). Ozdemir, A. I., Erol, I., Ar, I. M., Peker, I., Asgary, A., Medeni, T. D., & Medeni, I. T. (2021). The role of blockchain in reducing the impact of barriers to humanitarian supply chain management. *The International Journal of Logistics Management*, *32*(2), 454-478.

(46). Pant, K., & Palanisamy, P. (2025). Industry 4.0 in the Perspective of Supply Chain Management : Evolution and Future Research Agenda. *EMJ - Engineering Management Journal*, *37*(1), 52-70. Scopus. https://doi.org/10.1080/10429247.2024.2350287

(47). Perotti, S., Cannava, L., Ries, J., & Grosse, E. (2025). Reviewing and conceptualising the role of 4.0 technologies for sustainable warehousing. *INTERNATIONAL JOURNAL OF PRODUCTION RESEARCH*, *63*(6), 2305-2337. (WOS:001313269500001). https://doi.org/10.1080/00207543.2024.2396015

(48). Raza, F. (2023). AI for predictive maintenance in industrial systems. *Cosmic Bulletin of Business Management*, *2*, 167-183.

(49). Sanz, G., Pastor, R., & Domenech, B. (2018). A step-by-step guide to assist logistics managers in defining efficient re-shelving solutions for retail store deliveries. *International Journal of Physical Distribution & Logistics Management*, *48*(9), 952-972.

(50). Schlegel, D., Schuler, K., & Westenberger, J. (2023). Failure factors of AI projects : Results from expert interviews. *International journal of information systems and project management: IJISPM*, *11*(3), 25-40.

(51). Sharma, S., Gahlawat, V., Rahul, K., Mor, R., & Malik, M. (2021). Sustainable Innovations in the Food Industry through Artificial Intelligence and Big Data Analytics. *LOGISTICS-BASEL*, *5*(4). (WOS:000737189700001). https://doi.org/10.3390/logistics5040066

(52). Stoyanov, S. (2021). INTEGRATION OF ARTIFICIAL INTELLIGENCE IN THE SUPPLY CHAIN MANAGEMENT : INTEGRATION OF ARTIFICIAL INTELLIGENCE IN THE SUPPLY CHAIN MANAGEMENT. *Journal scientific and applied research*, *20*(1), 53-58.

(53). Toorajipour, R., Sohrabpour, V., Nazarpour, A., Oghazi, P., & Fischl, M. (2021). Artificial intelligence in supply chain management : A systematic literature review. *Journal of business research*, *122*, 502-517.

(54). Treiblmaier, H. (2018). Optimal levels of (de) centralization for resilient supply chains. *The International Journal of Logistics Management*, *29*(1), 435-455.

(55). Tseng, M.-L., Islam, M. S., Karia, N., Fauzi, F. A., & Afrin, S. (2019). A literature review on green supply chain management : Trends and future challenges. *Resources, conservation and recycling*, *141*, 145-162.

(56). Vakulabharanam, S. (2020). Optimizing Pharmaceutical Supply Chain Efficiency Using AI and Predictive Analytics. *Journal of Artificial Intelligence & Machine Learning Studies, 4*, 257-301.

(57). Verma, A., Lamsal, K., & Verma, P. (2022). An investigation of skill requirements in artificial intelligence and machine learning job advertisements. *Industry and Higher Education*, *36*(1), 63-73. https://doi.org/10.1177/0950422221990990

(58). Wang, X., Ma, L., Niu, Q., & Zhang, Y. (2024). Supply chain digitalization and sports industry performance in Chinese context : A mediated moderated model. *BUSINESS PROCESS MANAGEMENT JOURNAL*, *30*(7), 2213-2236. (WOS:001273126200001). https://doi.org/10.1108/BPMJ-10-2023-0776

(59). Zdolsek Draksler, T., Cimperman, M., & Obrecht, M. (2023). Data-Driven Supply Chain Operations—The Pilot Case of Postal Logistics and the Cross-Border Optimization Potential. *Sensors*, *23*(3). Scopus. https://doi.org/10.3390/s23031624

(60). Zhang, H., Liu, L. Z., Xie, H., Jiang, Y., Zhou, J., & Wang, Y. (2022). Deep learning-based robot vision : High-end tools for smart manufacturing. *IEEE Instrumentation & Measurement Magazine*, *25*(2), 27-35.

(61). Zhang, X., He, X., Du, X., Zhang, A., & Dong, Y. (2023). Supply Chain Practices, Dynamic Capabilities, and Performance : The Moderating Role of Big Data Analytics. *JOURNAL OF ORGANIZATIONAL AND END USER COMPUTING*, *35*(3). (WOS:001069314400001). https://doi.org/10.4018/JOEUC.325214

(62). Zoungrana, W.-B. A. B. (2020). *Application des algorithmes d'apprentissage automatique pour la détection de défauts de roulements sur les machines tournantes dans le cadre de l'Industrie 4.0* [PhD Thesis, Université du Québec à Chicoutimi]. https://constellation.uqac.ca/id/eprint/5857/