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Advancing supply chain management through artificial intelligence: a systematic literature review

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ABSTRACT

This study evaluates the role and impact of artificial intelligence (AI) in supply chain management (SCM). Following a five-step process, the review covered academic publications from 2000 to 2024, drawing from different databases. The review identified 426 relevant articles for analysis, focusing on AI techniques. The analysis explored their applications, advantages, and barriers to adoption in SCM. The study also discussed key challenges, including financial, organizational, strategic, technological, and legal barriers. The findings suggest that while AI techniques offer significant potential for improving SCM, several obstacles hinder their broader implementation. Addressing these obstacles requires investments in infrastructure, skills development, and effective change management.

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1. INTRODUCTION

In today's dynamic global economy, the field of supply chain management (SCM) faces unprecedented challenges and opportunities driven by technological advancements, notably artificial intelligence (AI) [1]. This paper delves into the transformative potential of AI within SCM contexts, aiming to elucidate its profound impact on operational efficiency, cost management, and risk mitigation across intricate supply networks. As industries navigate complexities exacerbated by globalization, market volatility, and sustainability imperatives, the integration of AI emerges as a critical enabler of adaptive and resilient supply chain strategies [2]. Traditional SCM frameworks confront escalating complexities amid a landscape characterized by rapid technological evolution and heightened customer expectations. Challenges such as demand variability, supply chain disruptions, and the imperative for sustainable practices necessitate innovative solutions capable of enhancing agility and responsiveness. AI technologies offer promising avenues to address these challenges by harnessing data-driven insights and automation capabilities to optimize decision-making processes and operational efficiencies [3].

Literature reflects a growing consensus on AI's transformative potential across diverse SCM domains. For instance, Khashei and Chahkoutahi [4] underscore AI's role in predictive analytics, facilitating accurate demand forecasting and inventory optimization. Similarly, Sari [5] discusses AI-driven autonomous systems that enhance operational efficiency and reduce lead times within warehouse management. Furthermore, recent studies by Lăzăroiu *et al.* [6] highlight AI's application in enhancing supply chain visibility through real-time data analytics, enabling proactive risk management and agile decision-making. These insights underscore AI's capacity to mitigate disruptions and enhance resilience amidst dynamic market conditions. This paper advocates for a comprehensive framework that integrates AI methodologies with established SCM principles to foster adaptive and intelligent supply chain ecosystems. By leveraging machine learning algorithms and advanced analytics, organizations can augment decision support systems, mitigate operational risks, and optimize resource allocation. The proposed approach emphasizes the strategic alignment of AI initiatives with organizational goals, advocating for a phased integration that prioritizes scalability, sustainability, and operational resilience.

This study contributes to the scholarly discourse by elucidating practical strategies and empirical evidence supporting the adoption of AI in SCM contexts. By examining case studies and empirical analyses, this research underscores AI's transformative potential in enhancing supply chain efficiency, reducing costs, and fostering innovation. The synthesis of theoretical insights with practical applications aims to empower stakeholders with actionable recommendations for navigating the evolving landscape of global supply chains.

2. METHOD

We applied a structured approach to our analysis, inspired by 5 steps process described David and David [7]. This approach began with a preliminary exploration of the literature to gain insight into the current research landscape. It also helped establish the parameters for selecting relevant publications, allowing us to refine the research and outlinethe subsequent phases. Our review involved five separate stages, which are presented in Figure 1.

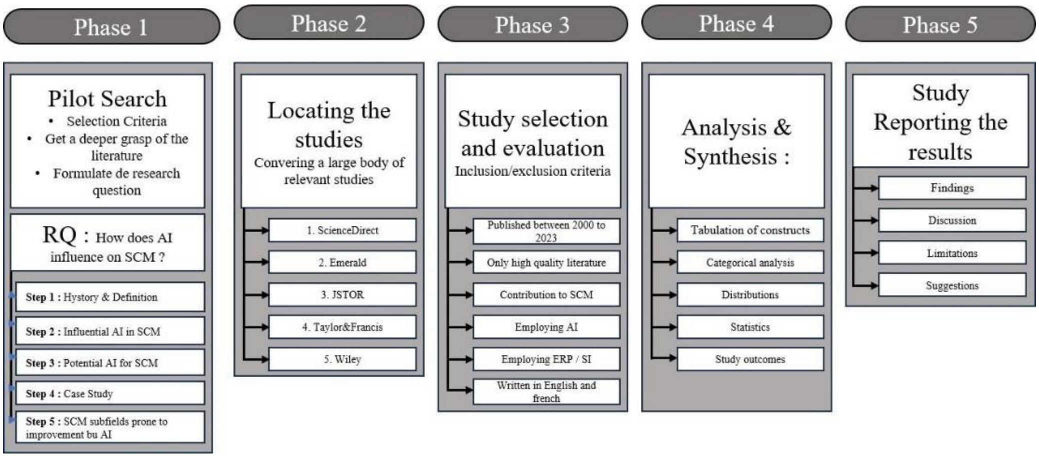

Figure 1. Study design

2.1. Search methodology

Following methodological rigor, a preliminary search was undertaken during the initial phase to enhance comprehension of the studied domain and extant literature. The identification of literature sources was ensured through systematic scrutiny of designated search parameters across diverse electronic databases of reputable publishers, including Scopus, ScienceDirect, SpringerLink, Web of Science, and Google Scholar. Articles were searched based on their title, abstract, keywords, and caption fields, encompassing all relevant fields. Keywords such as "artificial intelligence," "AI," "supply chain," "supply chain management," "SCM," "artificial intelligence applications," "production," and "logistics" were utilized to refine the search scope. The search was limited to articles published between 2000 and 2024 to focus on contemporary literature pertinent to the study.

2.2. Research questions

The formulation of a well-defined and actionable research question guiding the inquiry is a significant step [8]. Crafting such a question constitutes a pivotal, albeit challenging, facet of research design, as it not only steers the selection of research methodologies and strategies but also underpins the entire investigative endeavor [9]. This research's primary question, 'How does AI influence studies in the field of SCM?', was refined through iterative pilot searches. To provide a clear answer, the main question was broken down into three subsidiary research questions:

- What AI techniques are commonly used in SCM studies?
- What AI techniques could be applied to SCM research?
- What obstacles hinder the implementation of AI in SCM?

2.3. Locating the studies

In the pursuit of pertinent studies, meticulous selection of search engines and search strings was imperative. To ensure a comprehensive examination of peer-reviewed literature within a specified timeframe, we selected five prominent databases known for their broad coverage: Scopus, ScienceDirect, SpringerLink, Google Scholar, and Web of Science. We crafted search queries designed to extract the most relevant articles, following the guidelines set out by [10]. These queries were carefully applied across all five databases as shown in Figure 2. This approach helped us gather contributions that directly relate to our research question.

The search queries included combinations like "artificial intelligence" along with specific keywords such as "supply chain," "production," and "logistics". These keywords were derived from Stock and Boyer [11] detailed description of SCM. Although the primary search protocols were consistent across all databases, slight adjustments were made to account for the unique search algorithms used by each platform.

2.4. Papers selection

The pilot search yielded 2,940 articles. Two primary criteria were applied for selection: temporal relevance (limited to literature published between 2000 and 2024) in Figure 2 and adherence to standards of relevance and quality, thereby confining the review to peer-reviewed journal and conference papers. Additionally, a bespoke article inclusion protocol was devised, mandating adherence to three additional criteria: (1) English language proficiency, (2) central utilization of AI, and (3) contribution to the SCM domain. A meticulous screening process involving inter-rater reliability checks yielded a final selection of 426 articles for analysis and synthesis.

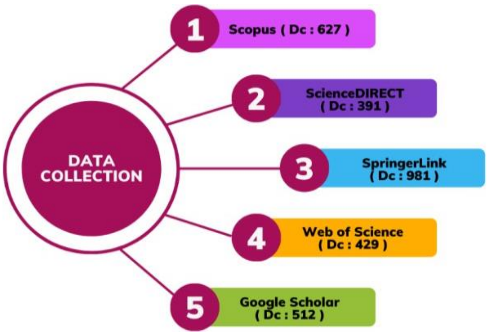

Figure 2. Database selection

2.5. Findings reporting

The selected articles were deconstructed based on specific attributes of the research question, including the field of SCM under study, employed AI techniques, and target industries for improvement. Synthesis efforts aimed at elucidating interrelationships among these attributes. In accordance with standard academic methods, this study's outcomes are communicated through a combination of tables, statistical evaluations, and comprehensive discussions. Following the approach described David and David [7], the results and discussions section summarizes the reviewed literature, pointing out both the well-established insights and the remaining gaps in understanding related to the research focus.

3. RESULTS

Out of the 426 articles selected for this review, 74 focused on logistics, 165 on production, and 186 on the broader field of supply chain. This review covers the period from 2000 to 2024, 68% were journal papers while 32% came from conference proceedings. The categorization of literature in the fields of logistics, production, and SCM is illustrated in the Figure 3. The literature is distributed as 46% focuses on production, 40% on the supply chain, and 14% on logistics. The logistics category includes topics such as container terminal operations, general management, inbound logistics processes, logistics systems automation, internet of things (IoT)-sizing, and logistics workflow. The production category covers areas like assembly lines and automation, production monitoring, integrated production management, manufacturing systems, quality control, product line optimization, workflow, and low- volume production. The supply chain category encompasses facility location, supplier selection, network design, risk management, inventory replenishment, crisis management, process management, planning and integration, and maintenance systems.

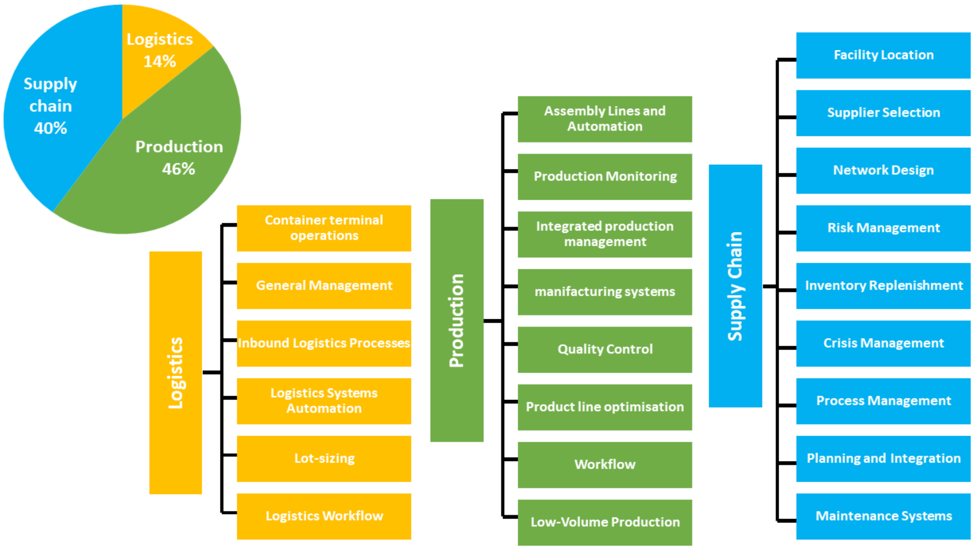

Figure 3. Summary of the categorization of the literature

The studies collected in this review reveal a comprehensive array of AI techniques employed across various domains as shown in Figure 4. Key techniques identified include association rule mining, automated planning, Bayesian networks, and case-based reasoning (CBR). Data mining and decision trees are prominent methods used for extracting patterns and making decisions based on data. Expert systems and fuzzy logic models are employed for handling complex decision-making scenarios and dealing with uncertainties. The literature also emphasizes the use of Gaussian models, genetic algorithms (Gas), and heuristics for optimizing processes and solving complex problems.

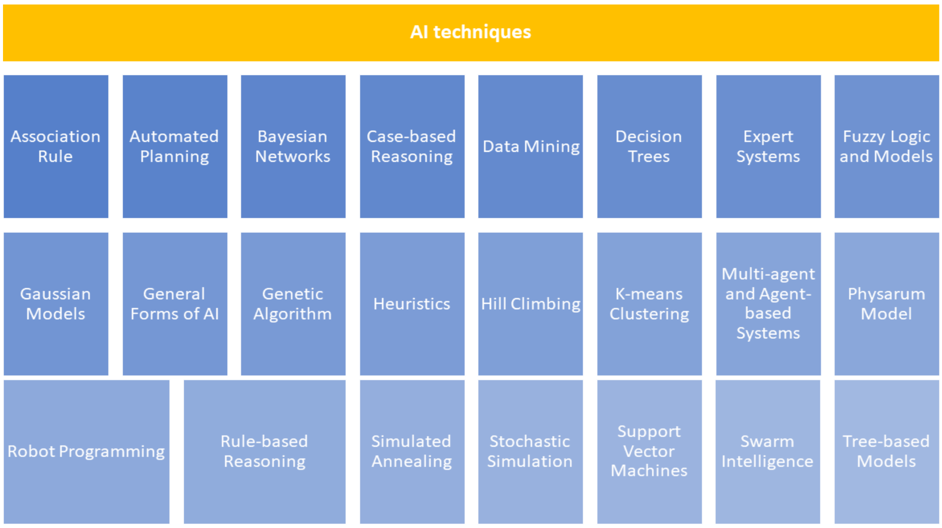

Figure 4. AI techniques

Advanced clustering techniques like K-means and multi-agent systems highlight the focus on organizing and analyzing large datasets. The review further identifies the application of innovative models such as the Physarum model and swarm intelligence, which draw inspiration from natural processes. Techniques like robot programming, CBR, and simulated annealing (SA) demonstrate the diversity in problem-solving approaches. Stochastic simulation and support vector machines are crucial for modeling and predictive analytics, while tree-based models are frequently used for classification and regression tasks. The studies showcase the extensive and varied use of AI techniques, reflecting the broad applicability and continuous evolution of AI in addressing complex challenges across different fields. The Table 1 summarizes the literature studies on AI techniques, their applications, and advantages across various domains like planning, sourcing, manufacturing, delivery, and returns in the context of SCM.

Table 1. Study collected summary

Techniques	Applications	Advantages	Studies
Planning			
Demand forecasting and planning	Using advanced algorithms like cohort intelligence and ANFIS to predict electricity demand	Increased inventory turnover	[4], [12]-[17]
Inventory management	Employing fuzzy hybrid intelligence-based seasonal models for electricity demand forecasting	Reduced out-of-stockscenarios	
Optimal inventory control	Utilizing machine learning techniques such as long short-term memory (LSTM) and support vector regression (SVR) for predictingvegetable retail demand	Improved inventorymanagement	
Sourcing			
Scheduling	Using SA algorithms and fuzzy logic controllers (FLC) to predict machine breakdowns	Reduction of productioncycle time	[18]-[20]
Manufacturing	Applying deep neural networks (DNN) and Markov decision processes (MDP) for dispatching	Optimized resourceutilization	[6], [21], [22]
Quality and Maintenance	Utilizing artificial immune systems (AIS) and FLC for machine prioritization	Improved early fault detection and better after-sales maintenance	[1], [23]
Delivery			
Inventory and stock management	Using linear regression, XGBoost, and random forest to forecast demand and manage warehouse inventory	Effective communicationwith customers	[24], [25]
Logistics and shipping	Automated concurrent negotiations with artificial bee colony algorithm	Reduction of transportationtime and costs	[26]-[28]
Shipping, process inquiry, and logistics optimization	Agricultural logistics optimization withGAs	Increase in customersatisfaction	[29]-[31]
Returns			
Network design	Remanufacturing logistics optimizationwith ant colony optimization (MACO)	Automation of return sorting and improvement incustomer service	[32], [33]
Collection activity optimization	Fuzzy logic and decision support systems for reverse logistics in a circulareconomy	Reduction in inventory carrying and holding costs	[34], [35]
Reverse logistics optimization	GAs for reverse logistics, routing, and network design	Increased environmentalsustainability	[36]-[38]

4. DISCUSSION

AI techniques encompasses the range of specific algorithms, system architectures, data structures, knowledge representations, and methodological approaches that can be clearly defined (as discussed by Bundy [39]). Our analysis began by identifying academic resources that list AI techniques from both a practical and theoretical perspective. Key references in this context include studies by Chen *et al.* [40], which investigated a variety of AI techniques and their applications, and the work by [41]. Bundy [39] work is also a key source, offering an extensive catalog of AI techniques that address a broad spectrum of needs. This section includes additional sources from varied origins, emphasizing the comprehensive scope of AI-related methodologies.

4.1. AI techniques

AI techniques have revolutionized the way complex problem-solving tasks are approached across various domains. Among the prominent AI methodologies are artificial neural networks (ANN), machine learning, expert systems, GAs, and agent-based systems. These techniques are particularly transformative in fields like SCM, where they enhance efficiency, accuracy, and adaptability.

ANNs replicate the brain's processes to tackle complex problem-solving tasks that are typically difficult for humans to address. They consist of interconnected nodes that process input data to generate outputs based on weights constantly improving through self-learning mechanisms. In the context of decision-making, at tactical and strategic levels operational research has long been applied since the 1980s for logistics, transportation, and operations planning. Today with increasing complexity and data availability in supply chain processes ANNs offer an approach compared to traditional operational research techniques tailored for individual sub-problems, within supply chain planning.

Since 2010, one of the notable applications of ANNs has been in supply chain planning. This application encompasses functions such as computing setup times, identifying ideal lot sizes for supply chain processes, and setting suitable inventory levels for both demand forecasting and production planning. Bruzzone and Orsoni [42] conducted a risk assessment wherein ANNs were employed to ascertain production cost loss and associated risks, in comparison to an alternative simulation-based methodology. The findings suggested that the chosen modular structure facilitated more efficient cost estimation and budgeting by enabling an ANN-based methodology.

Precise scenarios regarding production time, quantities, and capacities were inputted to the ANNs, alongside corresponding cost estimates/outputs. Drawing insights from these learning datasets, ANNs could establish relationships between inputs and outputs, thereby enabling cost estimations across various scenarios [42]. Zhao and Yu [3] applied ANNs to address the challenges faced by the supplier's CBR system. ANNs have a strong self-adaptive capability, which improves the accuracy of update phases and enhances decision-making in enterprise supplier selection. Jiang and Sheng [43] introduced an algorithm designed to enhance the selection of suppliers. Similarly, Chen *et al.* [44] investigated Bayesian learning techniques to examined supplier reliability, but their model's ability to be generalized to additional variables is restricted due to some excluded parameters. Garvey *et al.* [45] developed risk dependency graphs, which are adaptable for uncovering new insights and facilitating improved risk propagation modeling [46].

This means that this is a mathematical tool used to handle data that are indefinite, unsteady, imprecise, and noisy. It attempts to explain the concept of uncertainty by defining lower and upper approximations of original sets. Moreover, for it to be a decisive basis on which decisions can be made; this dynamic supply chain performance measurement has to be robust and agile. This problem is addressed by rough set theory. Supply chain measurements within a multicriteria decision frame were outlined in Zheng and Lai [47]. In monitoring upstream supply chain performance [48] it was used. For example, Bai and Sarkis [49] pointed out that rough set theory was employed in determining key performance indicators (KPIs) for supplier sustainability evaluations.

Another model has been developed by Zhan [50] regarding combinatorial judgment matrices based on objective and subjective judgment matrices. They defined their mining algorithm with criterion weighting as Geng and Liu [51]. Rough set theory was employed by these writers above for choosing the most appropriate supplier among several qualified ones using multiple yet conflicting suppliers' selection criteria.

Machine learning in Figure 5 is a method whereby a machine learns through the accumulation of experience rather than explicit programming to perform the task better by referring back to various data sources obtained from electronic backing. Machine learning classification can be broken down into three categories; supervised learning, unsupervised learning, and reinforcement learning. Predicting behavior is a crucial aspect of machine learning, particularly in its application to solving various challenges within supply chains. This predictive capability is utilized in both upstream and downstream management [52].

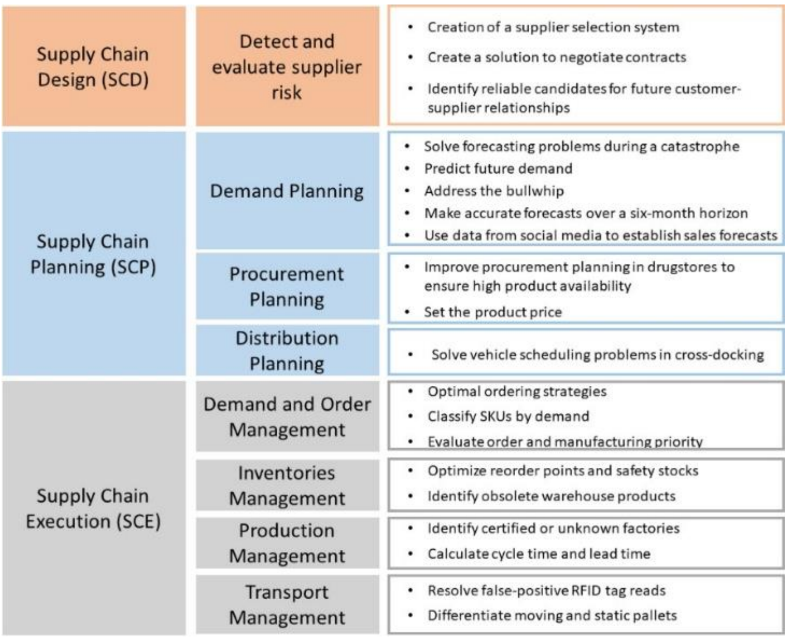

Figure 5. ML application in supply chain

Expert systems have proven to be effective across a range of domains, such as managing airline revenue and maintaining vehicles. They are also employed in air traffic control [53], demonstrating their versatility and potential applications in the supply chain domain. Notable uses of supply chain expert systems encompass supplier assessment; third-party logistics providers (3PL) selection; logistics strategy formulation; production scheduling and management; demand forecasting; evaluation of suppliers and subcontractors; and the development of a system for partner selection [5], [41], [54].

GAs in Figure 6 are search techniques that mimic the mechanisms of evolution and natural selection, where solutions to complex problems are evolved through a process of random variation and selection [55]. These algorithms have proven effective in addressing various challenging supply chain problems [41]. GAs were used to address traditional logistics challenges, such as facility layout planning [56]. They have been utilized to optimize inventory management [57]. GAs have helped improve the reliability of delivery services. They have been used to develop efficient freight consolidation methods. These algorithms have supported research in express courier service optimization. GAs have also been applied to aid in supplier selection during purchasing [58]. Jauhar and Pant [59] reviewed 220 research investigating the GAs application in supply chains. Their findings indicated that these algorithms are primarily used to manage production flow and improve order fulfillment processes.

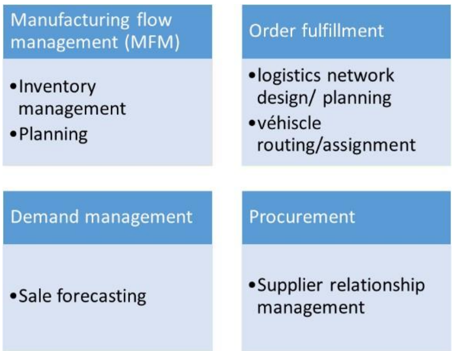

Figure 6. GAs application in supply chain

Those systems consist of autonomous entities, which can be processes, robots, or humans within a specific environment. These agents interact based on defined rules and exhibit a degree of independence. This characteristic makes them useful in supply chain performance monitoring and optimization. Various studies have highlighted the potential of agent-based systems in addressing supply chain issues. For instance, Du *et al.* [60] explored their use in dealing with demand fluctuations, while Lima *et al.* [61] focused on joint production planning. Chen and Wei [62] applied these systems to order monitoring and managing outsourcing relationships. Agent-based systems serve as effective simulation tools in inventory management, allowing for the modeling of complex interactions between various entities. They can help reduce costs and improve inventory fill rates, as demonstrated by Chan and Chan [63]. Additionally, these systems can model interactions between different inventory approaches, as seen in Ponte *et al.* [64].

Ghiassi and Spera [65] included contributions dealing with factors that affect the resilience of supply chain even indirectly, regarding supply chain relationship management, while Giannakis et Louis based on autonomous corrective actions towards improving the agility of supply chain. Supply chain coordination is a critical element, where insignificant fluctuations cause significant variations in orders upstream in the supply chain. The issue has been extensively researched, with Alzoubi and Yanamandra [66] offering various insights into supply chain performance improvement, lead time reduction, and strategies to minimize the bullwhip effect.

Zarandi *et al.* [67] examined ways to mitigate the bullwhip effect and reduce costs in multi-stage supply chains. They explored the benefits of improved coordination to achieve a smoother flow of goods and information. Additionally, Kwon *et al.* [68] delved into collaboration issues that arise from supply and demand uncertainty, highlighting the importance of effective partnerships among supply chain entities to tackle uncertainties and improve overall performance. In addition, some of the areas where there is a great deal of studying are collaboration between supply chain actors and across the supply chain that contribute to resilience and strength as against other competitors. Kwon *et al.* [68] have notably explored collaborative strategies to manage uncertainty within the supply chain. Pan and Choi [69] have focused on negotiating prices and delivery dates among supply chain partners, while Singh and Challa [16] have contributed to our understanding of information tracking throughout supply chains and e- supply chains. In addition, Dubey *et al.* [70] addressed supply chain resilience by proposing an agent-based approach. This approach involves monitoring key performance indicators to identify disruptions and evaluate appropriate mitigation measures.

4.2. Barriers of artificial intelligence on supply chain

The implementation of AI in the supply chain encounters several significant obstacles. Implementing Industry 4.0 initiatives requires substantial investment, yet many companies face financial constraints due to limited internal resources and a lack of external funding [71]-[74]. A significant hurdle is the uncertainty about the economic advantages of Industry 4.0, compounded by limited experience in key financial processes such as budgeting, cost analysis, and resource allocation [75], [76]. Additionally, businesses often lack effective risk management tools to guide investment decisions for Industry 4.0 projects [74].

Organizational barriers are a major challenge for many companies. Several studies have highlighted common obstacles that organizations face. There is a gap in the workforce's skillset, with many employees lacking the required competencies. The labor market also suffers from a shortage of skilled workers, and internal training programs are often inadequate. Organizations often struggle to adapt to technological advancements due to a lack of internal training and general resistance to embracing digital culture [73]-[76].

Many employees are not ready to adapt to new processes or technologies, showing high resistance to change [71]-[73], [75], [76]. Inefficient knowledge management and poor collaboration across departments and with supply chain partners can hinder organizational effectiveness. Several studies have investigated these challenges andsuggested ways to overcome them. Raj *et al.* [71] highlights the importance of robust knowledge management systems for effective organizational communication.

Industry 4.0 implementation faces several strategic barriers, which several studies have examined. Challenges with process changes and ineffective change management are commonly noted by [71], [74], [76]. Another significant barrier is limited commitment from top management, a point underscored by [72], [73], and others. A leadership gap can significantly impact lean production and continuous improvement efforts. They have observed that inadequate leadership correlates with shortcomings in lean practices and ongoing improvement initiatives. These studies suggest that when leadership is not aligned with lean principles, it can create obstacles to efficiency and innovation, leading to a stagnation in productivity and reduced competitiveness. To bridge this gap, organizations need leaders who prioritize lean production and foster a culture of continuous improvement.

Kumar *et al.* [72] and Nimawat and Gidwani [76] both noted that stakeholder involvement and engagement are insufficient in many instances. This shortcoming in engagement can result in a lack of clarity regarding the strategic significance of Industry 4.0, as Kumar *et al.* [72] mentioned. Furthermore, Stentoft *et al.* [73] highlighted that limited cooperation between academic institutions and the industry stifles innovation, indicating that stronger collaboration could be beneficial. An additional barrier is an overemphasis on operational aspects at the expense of research and development, which can impede Industry 4.0 adoption. The focus on this trend highlights the increasing demand for a more balanced approach [73], [74], [76].

Industry 4.0 brings significant technical and infrastructure-related challenges. A primary concern is the absence of strong digital and physical infrastructure, which is crucial for enabling data-centric services. This is compounded by inadequate broadband coverage, leading to disrupted data exchanges. Kumar *et al.* [72], and Majumdar *et al.* [74] have demonstrated how these issues hinder the flow of information.

Another challenge revolves around integration, including scalability, compatibility, and interoperability. The call for standardized solutions to address these integration issues has been echoed by [74]-[76]. Additionally, the slow pace of technological maturity has affected the broader implementation of Industry 4.0. Raj *et al.* [71], Nimawat and Gidwani [76] indicate the required technologies for Industry 4.0 that are still in their early stages, limiting thier widespread integration. Security and privacy concerns also contribute to the complexity of Industry 4.0 integration. Resistance to data sharing due to inadequate security measures creates additional obstacles. The need for robust data security is emphasized by [72], [74]-[76]. Addressing these issues is vital for promoting collaborative data exchange and facilitating Industry 4.0 implementation.

A critical issue is the inadequacy of legal measures to prevent cybercrime and data theft, which leads to vulnerabilities in protecting data and intellectual property. This deficiency in legal structures has been highlightedby [72], [74]-[76]. Furthermore, there's a notable absence of clear standards and government regulations in the realm of Industry 4.0, especially concerning labor laws, employment practices, data ownership, and copyright issues. This absence of formal guidelines results in uncertainty and confusion for businesses and employees alike. The need for comprehensive legal frameworks that address these issues has been emphasized by [75], [76].

5. CONCLUSION

ANN enable good SCM, but they do not offer a high level of precision, intelligence, initial configuration and process training. Due to financial constraints and organizational obstacles, the budget for ANN-based systems can be limited. Approximate set theory can be useful for managing the uncertain and the approximate, but in practice this can be done in a relatively clumsy way. Learning automation is crucial for accurately predicting SCM behavior, although its success depends on the quality of information and the determination of fairness and interpretability of decisions. Expert systems are structuring, but often suffer from flexibility in a turbulent and complex SCM environment.

Investigating the implementation of AI requires heavy investment in infrastructure and knowledge, which is resisted by the difficulty of accepting job losses and acquiring new technological knowledge. To overcome these obstacles, investment in infrastructure, the search for innovative momentum, the strategic design of roadmaps and regulatory compliance are all necessary. But the key to acceptance and optimization of the consequences of AI integration in SCM is employee training and change management. Agent technology is more than just mathematically optimized for the practical implementation of the ability to capture the phrasing of negotiation and coordination.

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