Research Trends and Knowledge Taxonomy of Artificial Intelligence Applications in Supply Chain Management, Logistics, and Transportation: A Systematic Literature Review and Bibliometric Analysis

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Abstract—**Due to industrialization and globalization, supply chains (SC) have become more and more in need of artificial intelligence (AI), which has sparked conversations on how to use it to improve SC performance globally. Using both quantitative and qualitative methodologies, this study provides a thorough examination of the trends, gaps, and knowledge structure in the literature on AI in SC. Scientific mapping was used to summarize 140 important publications published between 1998 and 2022. Publication years, attribution, journal co-citations, partnerships between countries and institutions, significant papers, related keywords, and historical study groups were all included in the bibliographic analysis. A thematic categorization of the data produced 22 sub-branches of AI application in SC that are covered in five domains: environment, planning and risk management, SC areas, technology, logistics and transportation, and planning and environment. The study identifies current knowledge gaps and recommends future research directions due to limited international cooperation and inadequate platforms for advancing technology research. these findings aid academics and practitioners by providing a coherent intellectual outlook on AI's involvement in SC.**

Keywords—Supply Chain; Supply Chain Management; Literature Review; Bibliometric Analysis; Taxonomy; Logistics; Risk Management; Transportation.

I. INTRODUCTION

In recent years, the purchasing, use, production, and distribution of products have all undergone substantial changes as a result of the introduction of cutting-edge technologies including big data, artificial intelligence (AI), blockchain, drones, the Internet of Things (IoT), 5G, robotics, 3D printing, biometrics, virtual reality, and augmented reality. The digitalization of almost all operational procedures brought about by these technologies has revolutionized supply chain management (SCM) by improving responsiveness, efficiency, and transparency [1] [2]. AI, in particular, has seen substantial advancements, fulfilling predictions made over half a century ago about its potential to converse with humans and mimic their skills [3] [4]. The contemporary supply chain network's organizational structure, operating procedures, and stakeholder interactions are becoming more dispersed, varied, and visible [5]. A growing number of people are interested in using artificial intelligence (AI), machine learning, and other intelligent technologies to address the difficulties and complexities of SCM in light of these developments [1], [6].

In spite of a large number of studies on AI applications in supply chain management, there are still gaps in thorough reviews and current evaluations in the literature. Prominent studies that have examined the advantages and difficulties of artificial intelligence in operations and SCM, like those by Fosso et al. and Helo et al., have offered fundamental insights [1], [6]. After doing thorough assessments of the literature, Toorajipour et al. and Riahi et al. identified both present-day and foreseeable AI approaches in SCM [7] [8]. The evolution of AI in SCM throughout history is highlighted in Pournader et al.'s literature review, which includes 150 academic articles [3], while Min (2010) examined AI subfields most suited for addressing real-world SCM issues [9]. However, these studies frequently fall short because of their restricted scope and obsolete data, which emphasizes the need for a more thorough and up-to-date assessment of AI applications in SCM.

By offering a thorough evaluation of the international literature on AI applications in SCM, investigating the state-of-the-art, pinpointing research hotspots, and monitoring developing trends, this study seeks to close these gaps. In particular, this study will monitor and assess the development of AI applications in SCM by looking at publications' year of release, their sources, the nations and businesses that are participating, their impact, and how keywords and research subjects are grouped. It will also identify research gaps and suggest potential future study areas, as well as develop a knowledge classification system based on scientometric discoveries.

The principal contributions of this study are the creation of an organized knowledge classification system for AI applications in SCM, which makes it easier to understand current research trends and opportunities, and an extensive and current review of AI applications in SCM, which addresses the disorganized and antiquated nature of earlier studies.

To improve clarity, the following research questions will serve as a guide for this study: What are the current trends and hotspots in AI applications within SCM? How have AI applications in SCM evolved over time in terms of publication year, sources, and geographical distribution? What are the most influential articles and key research topics in AI and SCM? What are the existing research gaps, and what future directions should be pursued in AI applications for SCM?.

The remaining is structured as follows: The outline of the methodology of research is presented in Section II. Section III presents the data gathering findings and the five elements of the scientometric analysis results.

On the basis of keyword clustering, Section IV provides a taxonomy for AI applications in SC research and goes into great depth on knowledge branches. Additionally, identified are the present research gaps and the objectives. The main conclusions and limitations are outlined in Section V.

II. METHOD

A. Review Overview Protocol

With the help of science mapping, this review-based study investigates the academic growth of international AI applications in SC research in a methodical manner. Science mapping is a quantitative analytical technique that uses mathematical statistics and graphical tools to look at bibliographic networks in a specific field. In Fig. 1, the entire process is displayed.

In this review-based analysis, we use science mapping—a quantitative analytic approach that examines bibliographic networks using mathematical statistics and visualization tools—to carefully evaluate the academic expansion of international AI applications in supply chain (SC) research. 140 papers are included for review after the procedure, which is depicted in Fig. 1, begins with an extensive search of the Scopus database. Relevant English articles and prestigious journals (ABS Ranking 3) are then selected. Keyword clustering and the display of international research collaborations, co-cited papers, and publications are all part of the investigation.

Step 1 is concerned with retracting statistics from the electronic Scopus database in its entirety. In addition to that, the most cited articles, journal distribution, and year publishing trend were all described.

In **step 2**, four scientometric tests were performed, including (i) co-citation analysis of the journals, which sought to pinpoint the most cited journals, as well as the study areas to which they belonged. By examining the distribution of published and cited journals in the investigated documents, this analysis seeks to determine the most significant journals in the field of SC research that have published publications about artificial intelligence applications [10]. (ii) analysis of country co-citation: This analysis aims to visualize the network of collaborative research in this field so that readers can get a clear picture of the collaborations between significant research communities and institutions worldwide. (iii) Co-citation analysis of articles: to draw attention to the important uses of AI in SC publications and the connections between references. The study of articles with lots of citations makes it simpler to understand the rising trend of academic interest in AI applications in SC. (iv) Keyword co-occurrence analysis: to visualize the hotspots of AI applications in SC keywords' co-occurred temporal zones and group them into several research topics. Through network analysis of co-occurring phrases, the knowledge structure of AI applications in SC is made clear. This technique is also used to highlight research hotspots and future research opportunities.

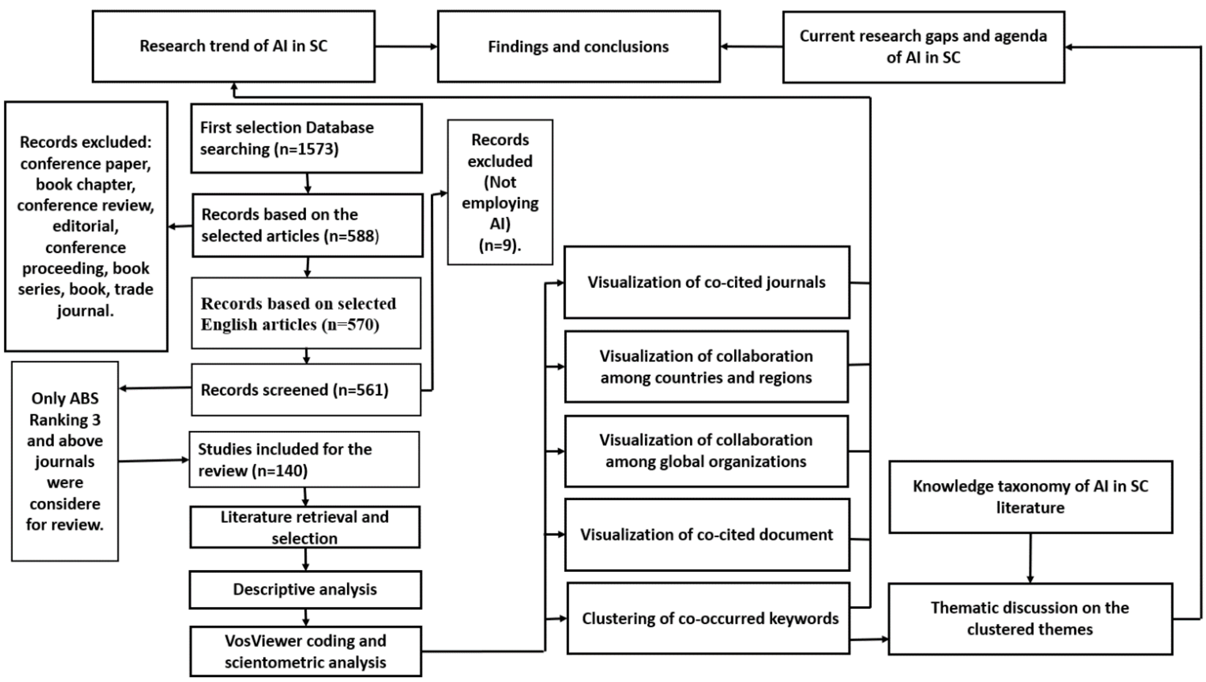

Fig. 1. The flowchart for evaluating AI applications in SC

Step 3 of the process offered the knowledge structure of the AI application in SC.

One important contribution made by VOSviewer is the creation of visual maps showing the interconnections between bibliographic entries. The strength of the connections between nodes is indicated by their distance from one another, while the size of the nodes reflects how frequently they appear. By distinctly distinguishing important journals, authors, keywords, and nations, the Total Link Strength (TLS) statistic of this tool improves the study by gauging the degree of association between nodes.

Vosviewer is an application that was developed by van Eck and Waltman (2010) [11]. The node stands for a particular bibliographic item. The node size depicts the relationship as the count of the evaluated items. Two nodes' estimated distance from one another demonstrates how closely they are related. When two nodes are built into networks, the program produces a statistic known as Total Link Strength (TLS), which quantifies the degree of correlation between them [12]. More extensive explanations of the Vosviewer's working mechanism are provided by Van Eck and Waltman (2014) [13]. The following objectives were achieved in this study by utilizing Vosviewer: The downloaded sample of Scopus literature must be loaded first. In the second step, the impact of notable journals, publications, nations and authors on the AI applications in the field of supply chain research is shown and analyzed [14]. Examining the connections between research keywords is the next step.

B. Literature Retrieval and Selection

Our data sources came from the Scopus database, which has coverage that is around 60% higher than the Web of Science (WoS) [8], [15]. "Artificial intelligence" and "supply chain" were the search terms we entered into Scopus as the first step in our literature search. Relevant English-language journal articles from 1998 to 2022 were found using this keyword search. To ensure the quality of the literature, we restricted our search to research articles exclusively and excluded conference papers, book chapters, conference proceedings, trade journals, editorials, book series, and book reviews.

To enhance our selection process, we limited our consideration to journals with an ABS ranking of 3, as these journals have a reputation for publishing unique and meticulously produced research papers, which is in line with the intellectual rigor needed for our study. These journals are also widely referenced. Additionally, the scientific community uses this ranking the most frequently [16]. Due to their practitioner-focused approach and publication of research that only satisfies a passable standard of quality, we eliminated ABS ranking 2 journals. Similarly, because ABS ranking 1 journal generally publish work with a modest threshold of rigor and quality, they were eliminated.

Using these standards, we were able to remove 1433 papers, leaving us with a final selection of 140 articles for our analysis, as shown in Fig. 1.

III. Scientometric Analysis Results

A. Publication by Years

Fig. 2 illustrates the number of papers published annually from 1998 through 2022. Evidently, until 2010, there has been a noticeable rise in research towards AI applications in SC after it had essentially stagnated since 2008. The brisk growth of academic research suggests that AI use in SC is becoming more widespread and diverse. Furthermore, there appears to be an increasing public awareness, market acceptability, and implementation of AI in this field, as seen by the rise in publications and the appearance of new issues linked to AI in SC.

The rise of AI applications in SC after 2010 has been fueled by a number of factors, though. An explanation for the spike in research activity may come from delving further into technical developments like the creation and improvement of deep learning algorithms, which have dramatically increased the capabilities of AI. More comprehensive and advanced AI research has also been made possible by economic reasons, such as increased funding from public and commercial sources. Furthermore, greater interest and creativity in applying AI to SC have been sparked by shifts in research priorities towards data-driven decision-making, which are being driven by the exponential expansion of big data and the demand for more effective and successful SCM.

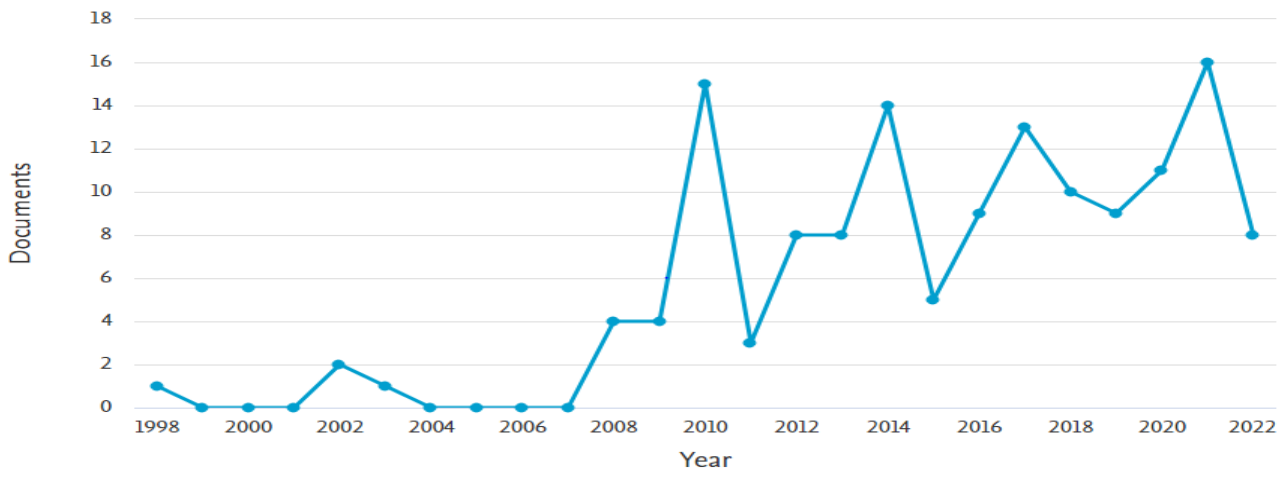

Fig. 2. Year Profile of Indexed Document

B. Analysis of Co-Citations and Journal Ranking

In 12 different journals, 140 articles were located. As depicted in Fig. 3, the top 5 journals contributed 116 articles, representing 82.8% of the overall. International Journal of Production Research ranks first (42, 30%), followed by Expert Systems with Applications (26, 18.5%), International Journal of Production Economics (19, 13.5%), Decision Support Systems (12, 11.4%), and European journal of operational research (13, 9,5%). All of the areas were chosen throughout the filtering process because the study's goal is to investigate how AI is applied in SC across all sectors and fields.

Finding the journals that were mentioned more than 20 times produced a network with 52 items and 985 links among the 140 publications, as shown in Fig. 4. Generally, there are four interrelated clusters made up of the journals that have an impact on supply chain (SC) research applications of AI.

The first cluster consists of the following journals: Management Science (TLS = 3,555, citations = 133), Decision Support Systems (TLS = 3,729, citations = 136), International Journal of Production Research (TLS = 17,551, citations = 455), and European Journal of Operational Research (TLS = 12,396, citations = 368). These publications provide quantitative methods for supply chain AI applications-related decision-making and optimization. Expert Systems with Applications (TLS = 6,083, citations = 184), the International Journal of Economics (TLS = 14,579, citations = 378), the Journal of Cleaner Production (TLS = 7,576, citations = 260), and the Journal of Operations Management (TLS = 4,529, citations = 103) make up the second cluster. These publications cover a wide range of topics related to supply chain research, including AI approaches, supply chain management, production planning and control, and supply chains.

The International Journal of Production Research (TLS = 3,191, citations = 84), Omega (TLS = 3,131, citations = 70), the International Journal of Production Economics (TLS = 3,604, citations = 124), and the European Journal of Operational Research (TLS = 1,964, citations = 51) are among the journals that make up the third cluster. Computers in Industry (TLS = 914, citations = 50) makes up the fourth cluster.

C. Analysis of Collaboration Countries/Organizations

Table I shows four metrics, including publications number (PN), TLS, average year of citation (AYC), and total citations (TC), for the countries that are actively researching AI applications in SC. The collaborative network between nations and regions is shown in Fig. 5. The minimum number of papers and citations required for a country to be included in the analysis has been set at five and thirty, respectively. A map containing 13 elements and 28 linkages was ultimately created.

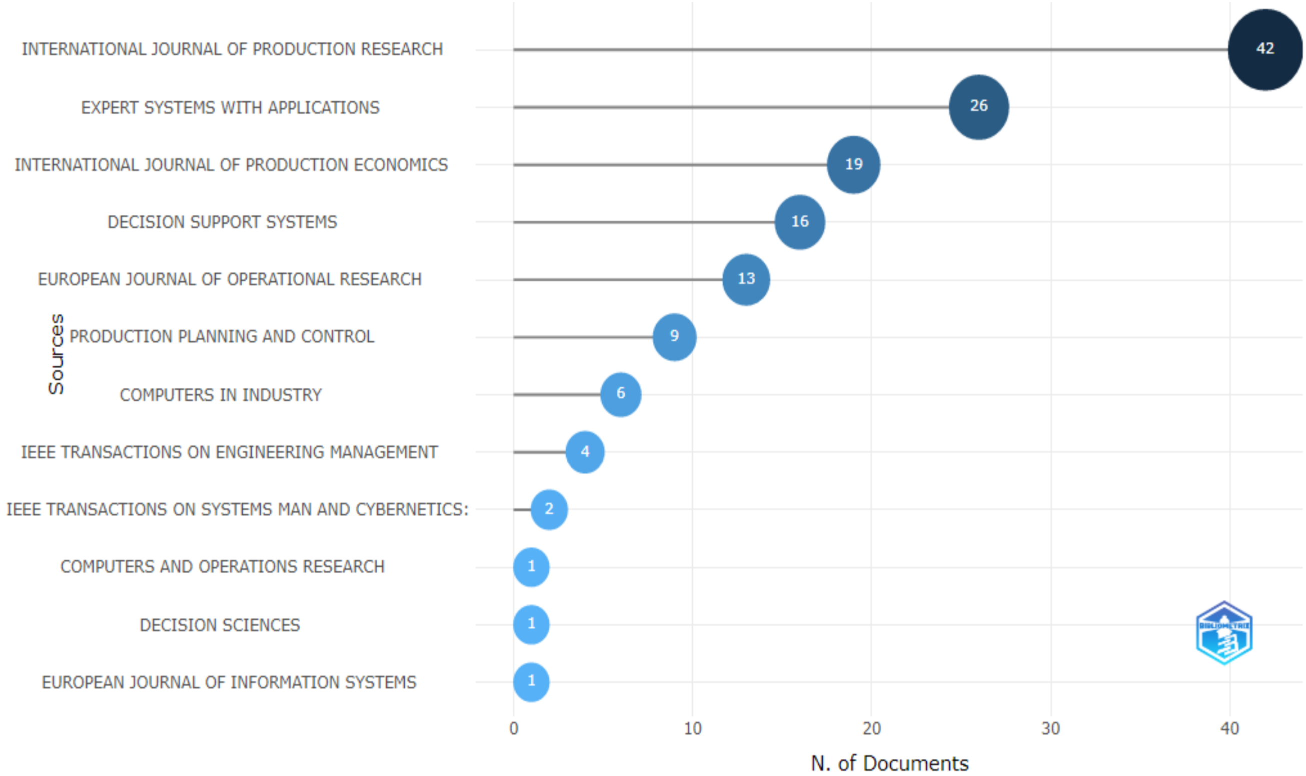

Fig. 3. Journal rankings for AI applications in SC publication numbers

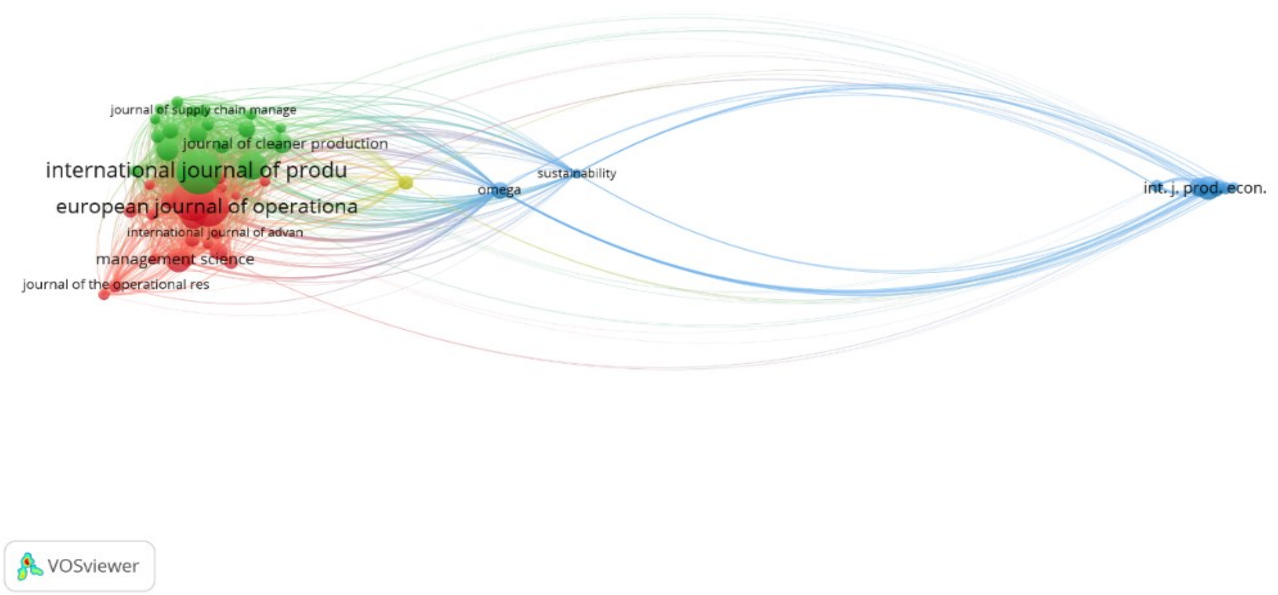

Fig. 4. Journals that co-cited mapping

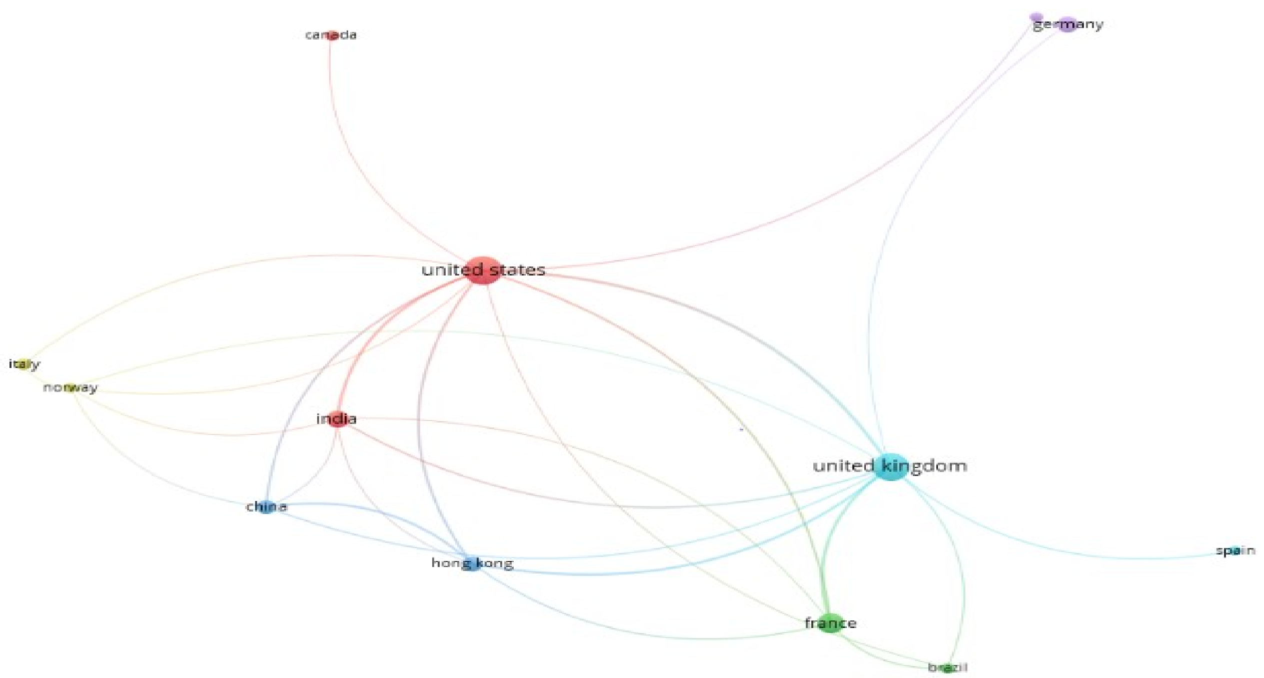

Fig. 5. A map of the nations and areas that support the use of AI in SC

TABLE I. THE NATIONS CURRENTLY USING AI IN SC

Country	Territory	PN	TLS	TC	AYC
United States	North America	41	37	2239	54.61
United Kingdom	Europe	38	35	1552	40.84
Hong Kong	Asia	12	19	540	45
India	Asia	15	17	546	36.4
China	Asia	11	16	383	34.82
France	Europe	20	16	916	45.8
Brazil	America	7	5	170	24.29
Norway	Europe	6	5	104	17.33
Netherlands	Europe	5	3	263	52.6
Germany	Europe	13	2	766	58.92
Italy	Europe	7	2	292	41.71
Spain	Europe	5	2	92	18.4
Canada	North America	6	1	81	13.5

According to Table I, AI application in SC research is widely distributed, especially in North America, Europe, and Asia. The United States has the most publications and the most TC.

Other nations like the United Kingdom, Hong Kong, France, India, China, and Germany present fewer PN. Additionally, the majority of the papers that these nations contributed were published within the last twelve years, indicating that they are becoming more actively involved in promoting the use of AI in SC.

In Fig. 5, we can see two arguments. First, four communities have been established based on cooperation for the global AI application in SC research. Two of the communities there are governed by European nations, like the United Kingdom and France, while the other two, "United States-India-Norway" and "China-Hong Kong," are respectively controlled by the USA and the UK.

Second, global cooperation is not important in AI application in SC research. Taking the USA international, where it collaborated with many countries to research AI applications in the SC, such as Canada, Italy, and India. Spain, Germany, and Canada publications have co-authors only with one country or region. This issue might be brought on by the stark variations in the history and paradigm of AI use in SC development among nations.

Additionally, the research continues to concentrate on the specialized areas of each researcher, like logistics [17], [18], production [19], [20], and supplier selection [21], [22], as a result of the knowledge gap brought on by the widespread extension of AI applications in SC and the dispersed knowledge structure. Consequently, there hasn't been much cooperation to date between academic institutions with disparate backgrounds.

Fig. 6 depicts the network of 9 elements and 36 links that was constructed from the 354 organizations that contributed to the application of AI in SC research. More than three articles have not been published by any of the organizations. Consequently, it can be contended that no organization has been capable of taking the lead on AI application in SC research thus far. Nonetheless, several organizations in Europe, the USA, and Asia have a better reputation in AI applications in SC due to higher citations, including the Robotics Institute (Hong Kong, 628 citations), Walter (The Netherlands, 628 citations), School of Businesses and Economics (Greece, 268 citations), Victoria Businesses School (Taiwan, 250 citations), Operations and Supply Chain Management (USA, 250 citations), Industrial Engineering (USA, 250 citations) and Entrepreneur (Singapore, 222 citations). Additionally, Fig. 6 demonstrates a lack of cross-organizational collaboration in research.

Additional investigation into how national research funding rules affect collaboration patterns may shed light on the reasons why particular nations lead the way in SC research with AI applications. Analyzing institutional priorities and their influence on research agendas might help explain why various areas and institutions collaborate in very different ways. Understanding these cultural differences could aid in explaining the observed cooperation tendencies. Cultural attitudes toward academic collaboration also play a vital influence. The amount of cross-country and cross-organizational partnerships is heavily influenced by economic incentives and restrictions, such as financing availability and intellectual property regulations. The economic elements that either support or impede collaboration can be identified and addressed to provide methods for more integrated and cohesive international research endeavors. A more thorough investigation of these underlying causes would enhance the conversation and offer a more thorough grasp of the dynamics guiding AI application research in SC across various nations and organizations. By examining these areas, we may develop strategies to enhance collaborative efforts in AI applications in SC research and acquire a more profound comprehension of the variations in global cooperation.

Fig. 6. An overview of the organization's international partnerships that support the use of AI in SC

D. Analysis of Significant Documents

The co-citation network was built after the most significant AI application in SC publications over the previous 24 years was examined using the co-citation of documents. As depicted in Fig. 7, a common visual network map was created using VOSviewer, with a minimum citation requirement of 30 to build a common visual network map of 60 elements and 188 links. The nodes on the map represent the papers defined by the name of the original author and the year of publication. The nodes' colors and links' colors correspond to the co-cited papers' publication dates and times, respectively. The co-occurrence of the publications demonstrates a clear type of "local concentration and general diffusion," demonstrating that some AI applications in SC research were generally accepted and created some common concepts and outcomes. The majority of publications with a high number of citations were published in 2010, a significant year for the use of AI in SC research. The co-citation time series indicates that AI application in SC knowledge spreads faster and faster.

Table III (Appendix A) lists the top 15 most highly cited papers, including their publication year, title, TLS, source, number of citations, and topic areas. The study with the most citations was by Swamithan et al., a simulation-based framework for creating unique supply chain models from a library of software components was described [23]. Tako et al., are the second, and their primary contribution is to explore the application of DES and SD as decision support systems (DSS) for LSCM by looking at the nature and level of issues modeled [24]. The third is Dweiri et al., whose main contribution is to propose a decision support model for selecting suppliers according to the analytical hierarchy process [22]. These were followed by Zimmer et al., whose main contribution is to concentrate on formal models to aid in decision-making for sustainable supplier selection, tracking, and development [25]. followed by Baryannis et al., whose main contribution is to give a thorough assessment of supply chain literature that addresses issues pertinent to SCRM utilizing approaches from the field of artificial intelligence [26]. Other highlighted documents' primary subjects include: (i) to comprehend the future directions of the agri-food domain, a review of more than a hundred publications on new technologies and the new accessible supply chain approaches are studied [27]; (ii) For the challenge of sustainable supplier selection, this work offers a decision support system [28], closed-loop supply chains [29], suggests a clever decision support system architecture for scheduling and production monitoring in remote manufacturing environments using radio frequency identification [30], review [31], Multi-objective product optimization for a four-tier supply chain architecture that includes suppliers, manufacturing facilities, distribution hubs, and customer zones [32], the use of BDA-AI for decision-making in dynamic situations and, in doing so, make some original theoretical and practical contributions to management [33], describing a method for managing inventory decisions throughout the entire supply chain in an integrated way [34], risk management [35], Closed-loop supply chains [36].

Furthermore, recognizing and talking about new themes in AI applications for supply chains, such as how AI may be incorporated into sustainable supply chain operations or how AI affects supply chain resilience, might point to areas that need more research. Acknowledging unaddressed subjects, such as the moral ramifications of artificial intelligence in supply chains or geographical differences in AI adoption, would also improve the study's comprehensiveness. Examining these facets may yield a more comprehensive and equitable comprehension of the present situation and potential future paths of artificial intelligence implementations in supply chain investigations.

E. Co-occurrence Keyword Analysis

To determine present and emerging trends, as well as the internal organization and focus of AI applications in supply chain management, a co-occurrence analysis of keywords was carried out [10]. The "All Keywords" and "Full Counting" VOSviewer analysis settings were utilized to obtain a thorough conceptual landscape of AI use in supply chain (SC) study. Setting the minimum number of occurrences of each keyword to four resulted in the creation of a network with 64 nodes representing keywords and 2,859 links, as illustrated in Fig. 8. Fig. 8 breaks down the top search terms used in AI applications in SC into five groups, each indicated by a different hue, and shows the co-occurrence relationships between these phrases.

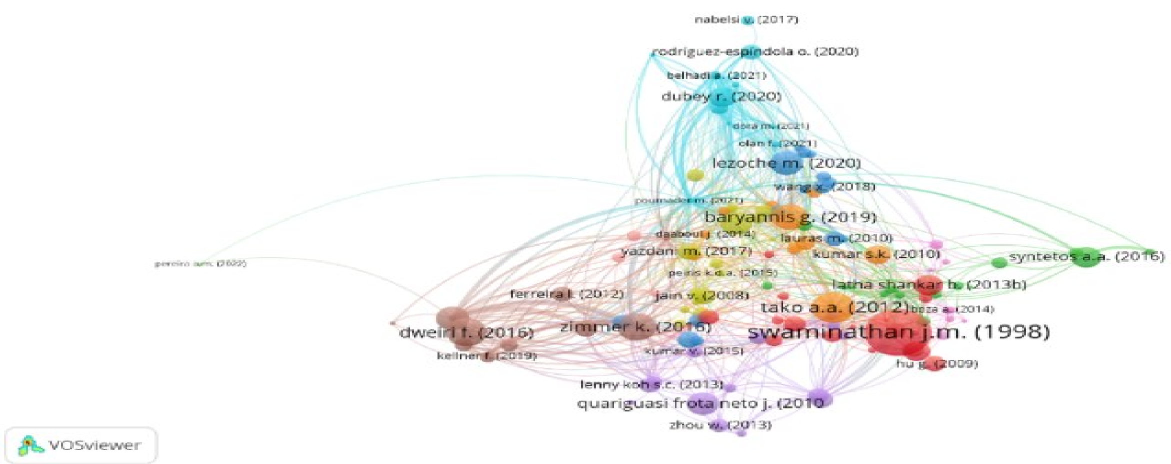

Fig. 7. The connection between the significant papers' co-citations and their mapping

The 18 components that make up Cluster #1 are concentrated on food supply, AI applications, and supply chain management networks. With regard to the supply chain and its industries, including manufacturing, transportation, and logistics, Cluster #2 includes 17 components. Decision support systems, supply chain management, and decision-making are the three main topics covered by Cluster #3, which has twelve components. AI methods like machine learning and decision trees are the focus of Cluster #4, which has ten elements. Lastly, the seven pieces that make up Cluster #5 are focused on supply chain management, production control, scheduling, and decision support systems.

Table II offers comprehensive details on the important keywords. Artificial intelligence (Frequency = 143, TSL = 772), supply chains (Frequency = 92, TSL = 536), decision support system (Frequency = 91, TSL = 536), supply chain management (Frequency = 72, TSL = 406), decision making (Frequency = 48, TSL = 325), decision theory (Frequency = 54, TSL = 330), optimization (Frequency = 25, TSL = 162), manufacturing (Frequency = 21, TSL = 149), and forecasting (Frequency = 21, TSL = 149) are the top ten most frequently examined and highly related keywords. The development of research themes for AI applications in SC and the bridging of the major academic fields depend heavily on these keywords. Keywords like artificial intelligence, supply networks, decision support systems, and decision making have attracted a lot of attention, according to the average citation measure.

The growing relevance of improving decision-making capabilities in supply chain management is shown by the clusters linked to AI techniques like decision trees and machine learning, as well as decision support systems. This pattern indicates that in order to optimize supply chain operations, future research will concentrate on creating increasingly intricate and integrated AI systems. Moreover, the existence of manufacturing and logistics-focused clusters suggests a persistent interest in enhancing operational effectiveness. Recognizing new areas, such as the use of AI to resilient supply chain models and sustainable supply chain practices, can be facilitated by an understanding of these clusters. Researchers can more successfully foresee and handle the opportunities and difficulties in the field of AI applications in supply chain management by looking at these term clusters.

TABLE II. AI APPLICATIONS IN SC RESEARCH: RELEVANT KEYWORD SUMMARIES AND THEME CLUSTERS

Cluster-ID	Keywords	Occurrence	TLS
Cluster #1 (red)	Artificial Intelligence Sustainable development Product design Supply chain network Food supply chain Sustainable Supply Chains	143 11 9 9 8 7	772 76 70 62 48 53
Cluster #2 (green)	Supply chains Optimization Manufacture Costs Integer programming Algorithms	92 19 14 11 10 9	536 131 97 89 67 65
Cluster #3 (blue)	Decision support systems Supply chain management Decision making Decision theory Decision supports Sensitivity analysis	91 72 54 21 14 9	536 406 330 149 101 57
Cluster #4 (yellow)	Forecasting Competition Inventory control Commerce Learning systems Risk management	10 6 7 6 7 5	64 51 49 45 36 31
Cluster #5 (purple)	Decision support system Decision support system (dds) Scheduling Radio frequency identification (rfid) Administrative data processing	25 10 7 6 5	162 67 43 35 38

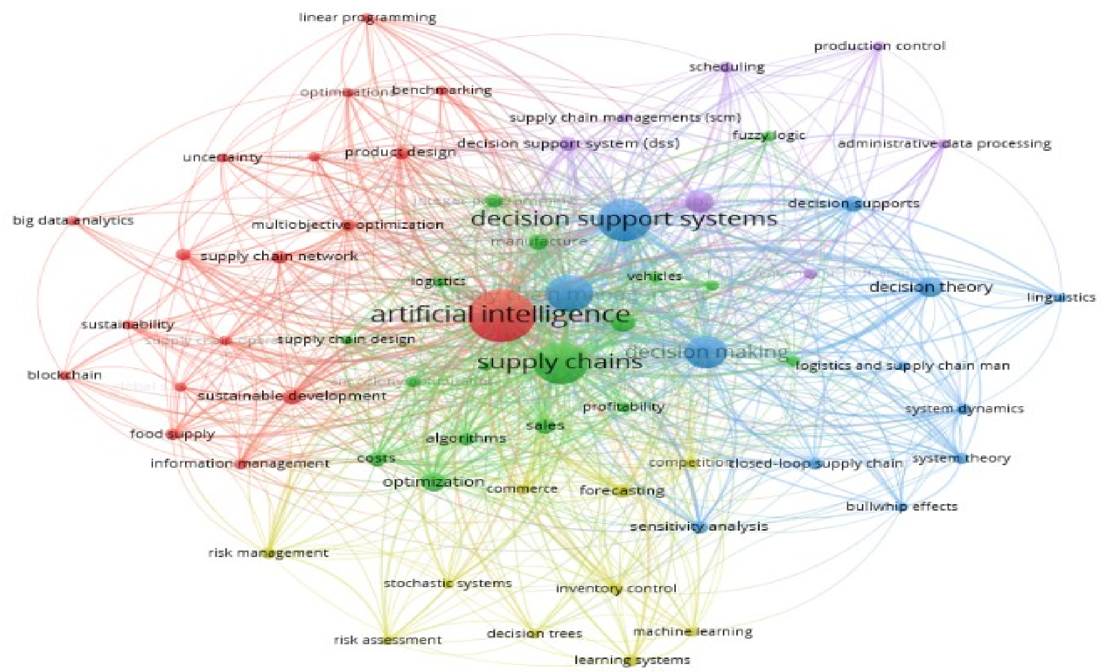

Fig. 8. Co-occurring keywords' mapping

IV. Discussion

A. The Classification of Knowledge

The analysis above clarifies the evolution of the research, its general trajectory, and some frequently debated issues surrounding AI use in SC. However, the general scientometric analysis's findings can't fully capture the explicit division of the varied body of knowledge in a particular field [10], [37]. A thorough taxonomy AI application in SC knowledge from 1998 to 2022 was also proposed based on the clustering analysis of high-frequency keywords, and each separated branch was then thoroughly and thematically examined. The taxonomy was manually renamed and merged into many sets of themes in order to make it more comprehensible and succinct. In Fig. 9, where a total of 5 alignments and 22 subbranches have been formed, AI application in SC research themes is illustrated.

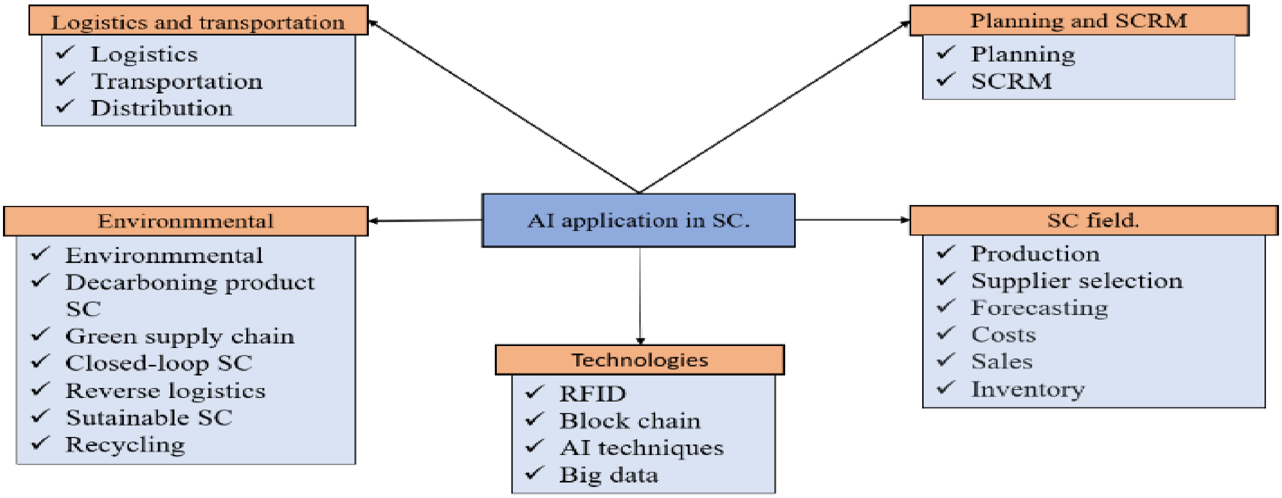

Fig. 9. The SC AI application's knowledge taxonomy

1) *Environmental and impacts of artificial intelligence in the supply chain:*

Numerous studies have examined and addressed ways to enhance future green supply chain activities. These research ideas were inspired by seven factors: environmental, sustainable SC, closed-loop SC, recycling, reverse logistics, and decarbonization. To improve knowledge of the interaction between external and internal GSCM operational aspects, he developed [38] a comprehensive taxonomy of green SCM methods and a support or decision system driven by structural equation modeling. Research of different management approaches was offered by Giacomo et al. [39], who also determined the best way to carry out rigorous environmentally sound management strategies. A supplier selection model that supports the cooperative CO2 reduction tool was presented by Sebastian Theißen et al. [40], and Lenny et al. [41] provided a thorough and practical evidence-based framework to help with decision-making to decarbonize the supply chain. For carbon price variation simulations, Hongto Ren [42] built a random two-stage MIP model and paired it with a GBM model. Kurt, then connected the production of hazardous waste in one industry to the indirect demands that drive the production of hazardous waste elsewhere. Hu (2009) [43] applied the idea of a sustainable product life cycle system to the manufacturing process and created a system for the evolution of products based on random dynamic programming. Femi olan [44] investigated alternative supply chain networks for foreign direct investment using AI theory; the results of his research point to the potential benefits of AI-driven supply chain networks for sustaining the flow of food and beverage supply chain finance. To create a sustainable mask for the first time during the COVID-19 outbreak, Tirkolaee et al. [45] have created a new sports model. Kumar (2017) [46] developed a multi-level logistics model with a vehicle-oriented, backward, and forward logistics system, this model is solved by using artificial immune system algorithms and particle swarm optimization. Lechner, and Gernal (2019) [47] discussed the integrated decision-making process in reverse logistics, product quality classification, and reprocessing disposal.

2) *Planning, and SCRM Research of AI application in SC:*

We discuss two important uses of AI in this paragraph: SC planning and supply chain risk management. Initially, Baryannis [26] offered a thorough examination of SC literature that applies AI methods to SCRM problems. As part of the Reactive Disaster and Supply Chain Risk Decision Support System, Frank Schätter [48] developed a novel decision support method to improve Business Continuity Management for significant interruptions brought on by disasters. A two-stage Decision Support System was introduced by Riccardo Mogre [49] to assist managers in choosing risk mitigation techniques for supply chain risks and resolving problems as they emerge.

In order to assist managers in selecting appropriate risk policies and making staff planning decisions in the face of uncertainty, Susanne Wruck [50] created a decision support tool that analyzes risk optimization strategies and predicted value-based optimization. David Bogataj [51] suggested a novel use of the Extended MRP model to regulate perishability in real-time.

In the field of SC planning, Hector Flores [52] concentrated on creating and organizing agri-food supply chains in order to find profitable venture prospects. The development of DSS, such as commercially accessible advanced planning systems, for hierarchically structured planning techniques was covered by Kasper Bislev Kallestrup [53] . Due to its encouraging outcomes, Brevik Elisabeth [54], emphasized the application of an optimization-based decision support system employing the Mixed-Integer Programming model in a case company. Using a linearized transfer function and a PID and LQR controller architecture, Hicham Sarir [55] created a plan and a methodical design process for production and inventory control.

3) Fields of the supply chain:

a) Production

A DSS that combines human and machine decision-making was proposed by Baptiste et al. [20] to schedule manufacturing and the semi-trailers needed for transport simultaneously. A DSS with an improved mobile scheduling system was introduced by Parviz Ghandforoush et al. [56] to support the platelet production SC. Two decision support tools using monolithic and hierarchical models were provided by Wen Yang et al.[57]. Mustafa Cimen et al.'s numerical trials [58] show how well-performing policies created with temporal difference ADP algorithms work.

b) Supplier selection

The selection of suppliers is a critical factor in the success of any organization, as they are the first and main source in any SC. In Pakistan, a poor country, Fikri Dweiri et al. [22] presented a decision support model for supplier selection in the automotive sector. A novel method for ranking and assessing suppliers was presented by Luciano Ferreira et al.[21]. It mixes fuzzy logic with an influence diagram. A Decision Support System and models were created by Sencer Erdem et al.[59] to improve supply chain decisions on supplier assessment and order allocation. An enhanced methodology integrating multi-objective optimization with the analytic network process was presented by Florian Kellner et al. [60] to satisfy sustainability criteria in supplier portfolio configuration.

In order to develop a decision support system for sustainable supplier selection in the actual textile sector of India's rising economy, Devika Kannan et al.[61] proposed a three-phase technique.

c) Forecasting

For SC managers, projecting demand accurately presents a big challenge. Neural network applications to supply chain data and rigorous simulations to identify optimal circumstances were proposed by Konstantinos I. Nikolopoulos [62]. Furthermore, an empirical examination using data from automobiles showed that practitioners could gain from using supervised NN approaches.

d) Costs and sales

In Hong's work, an integer-programming model was established for a distribution-allocation problem in a two-stage supply chain with fixed costs. An Ant Colony Optimization (ACO)-based heuristic was devised to address the problem [63]. When deciding on inter-echelon quantity flow in a supply chain for a single planning horizon, Kumar [35] identified a number of operational risk factors, their predicted values, and probabilities of occurrence, as well as related additional costs. The findings demonstrated that by improving the capacity to react to changes in risk factors, the suggested approach helps to create a resilient SC architecture.

e) Inventory

One of the main challenges in inventory management is coordinating inventory policies among various supply chain participants, including manufacturers, distributors, and suppliers. The goal of this cooperation is to efficiently manage the flow of materials, reduce expenses, and promptly satisfy client demands [34]. An integrated approach to inventory decision-making across the whole supply chain was outlined by Ilaria Giannoccaro [34]. The goal of Christian Mascle's [64] research is to offer a paradigm for reliable sales planning in small enterprises, where a multitude of product variants contribute to complexity. A fuzzy logic-based decision-support system was presented by Peter Wanke [65]. to take into consideration inventory carrying, shortages, ordering, and transportation costs. Two approaches to inventory control were proposed by Hicham Sarir [66] : the PIDACO strategy-based method and the fuzzy logic approach-based method.

To estimate future demand and choose the best inventory policy values for each node in a supply chain network, T. Warren Liao et al. [67] suggested combining metaheuristics with exponential smoothing approaches.

4) Technologies:

AI, Blockchain, RFID, and big data innovations in recent times have showed promise in solving a range of supply chain system problems. Operations and supply chain management (SCM) research has been led by advances in machine learning, artificial intelligence, and big data analytics [33]. Genetic algorithms can lessen the bullwhip effect and help supply managers estimate reorder quantities across the supply chain, as T. O'Donnell [68] showed. The Ant Colony Optimization approach was revised by Indra Eluubek Kyzy et al. [69]. According to Dubey et al. [33], the results of data analysis indicate that entrepreneurial orientation (EO) is essential for maximizing the potential of BDA-AI in order to get improved operational performance. An intelligent DSS architecture based on RFID was presented by Guo et al. [30] to handle scheduling and production monitoring in a remote manufacturing environment.

In our data base existed many studies that have used AI technology; such us Genetic Algorithms [32], [38], [54], [65], [70], [71], [72], [73], [74], [75], [76], [77], [78], [79], [80] , Particle swarm optimization [35], [46], [63], SMART algorithm [34], [81], Nearest neighbor [62], [82] , Artificial immune system algorithm [83], [84], ANN (Artificial Neural networks) [65], [85], GNN (Graph Neural Networks) [86], Neural networks [87], Hybrid Technique [45], Ant colony optimization [69], SVM (Support vector machine) [88], Fuzzy Wavelet Neural Networks [89], Artificial WD [96], DN (Dimensionality Reduction) [52], C4.5 algorithm [73], Kalman filter [90], Clustering [91], Adaptive tabu search (ATS) algorithm [99], Decision tree [94], Bayesian networks [85], Particle swarm intelligence [92], Regression trees [93], Bioinspired algorithms [95], Multi-objective artificial bee colony [96], Intelligent agent [100], Intelligent optimization algorithms [30], Association rule mining [98], and Ant colony [67], [101].

5) Logistics and Transportation:

Systems engineering classics include transportation-related difficulties [102], [103]. Cumulative vehicle routing issue and multidepot vehicle routing problem were integrated by Xinyu Wang et al. [104] to form cumMDVRP, an integer linear programming model for emergency transportation scenarios during natural disasters. Shida et al. [105] addressed transportation vehicle scheduling issues in SCM by presenting a modified version of the Modified Transition Probability Operation Method, Varying Dimension Matrix Encoding, and Ant Colony Optimization with Negative Selection Operation.

The logistics and supply chain environment is characterized by competitive global markets, quickly growing technology, and increasing market complexity [106]. The rising application domains and depths of autonomous systems in logistics bring new difficulties for the study and creation of human-machine interaction concepts [107]. V. Aror [108] presented a quaternary policy system for integrated logistics and inventory in supply chains, using dynamic ant colony optimization to establish delivery vehicle pathways. Moncayo-Martinez [97] devised a modified multi-objective extension of the Intelligent Water Drops (IWD) algorithm to provide a pareto set for tackling logistics network difficulties. S.L. Ting [98] presented the Supply Chain Quality Sustainability Decision Support System, utilizing Dempster's rule of combination and association rule mining to help managers in food manufacturing organizations create effective logistics plans to ensure product quality and safety. Dirk Werthmann [109] provided a case study concentrating on optimizing finished vehicle logistics utilizing electronic product code information services and RFID-based systems (EPCIS). Morteza Yazdani [17] proposed a decision support model based on the deployment of the quality function and the strategy for order preference by similarity to an ideal solution for the French agricultural supply chain.

B. Research Gaps and Agenda

The complete research trend, popular academic subjects, and knowledge taxonomy of AI application in the SC domain were made clear by the scientometric study and theme discussion discussed above.

There are still certain issues that need to be addressed in future studies, despite the fact that scholars and practitioners have made significant progress in boosting AI applications in SC.

1) International Cooperation for SC AI Application:

International cooperation in research models is still insufficient. The generalizability of the majority of AI applications in SC fields that are based on local situations requires further study. Due to a lack of global solutions, lack of international cooperation, and communication obstacles, there is an imbalance in the use of AI globally in SC fields. Additionally, the current achievements are insufficient to encourage the internationalization of AI in SC.

Under the trend of AI application in SC, it is necessary to improve cross-institutional, industrial metrics, technological innovation, and macro development strategies in order to close this gap. For instance, more empirical research is required in some developing nations in the world, given that their economies are expanding quickly and that their populations and demands are higher.

2) Subfields of SC and AI:

Despite significant progress in AI research specifically related to supply chain management, there is a need for more comprehensive, holistic research to further enhance our knowledge of and use of AI in this area. Research on AI in SCM is complex and multi-faceted, involving many interconnected variables and having significant impacts. Currently, the application of AI in supply chain management is largely focused on analyzing specific, one-directional relationships, such as supplier selection, production, and inventory planning. However, AI has great potential for future developments in this area.

AI has contributed significantly to the development of many fields of SC. Our results show that the fields of the supply chain that focus frequently on the application of artificial intelligence are as follows: production, supplier selection, forecasting, inventory, costs, and sales. However, less emphasis is placed on costs, sales, and forecasts. In general, Overall, sales, costs, and forecasting are fields that can be further improved through the use of artificial intelligence techniques. The fields of logistics, including distribution and transportation, healthcare logistics, logistics hub management, and logistics risk management, are likely to benefit from AI techniques due to their practical potential and the current research gap in these areas [7]. Additionally, Green SC practices deserve additional attention from the perspective of AI techniques because of their vital significance in environmental preservation.

3) AI techniques application in SC :

AI, one of the most notable industry 4.0 technologies, has the potential to revolutionize a wide range of sectors and industries [7], [110]. Among many areas, the SC fields are vulnerable to the influence of AI techniques. This study showed that there are a large number of AI technologies applied in the SC, yet only a few are explored and exploited in the supply chain. In our study, Algorithm, Dimensionality, Decision tree, Fuzzy Wavelet Neural Networks, Graph Neural Networks, and others, are techniques that are made use of in Sc. However, GA, and swarm immune intelligence are the most prominent ones. Moreover, in the outcomes of our research Robotics, Knowledge Representation, Natural Language Processing, and MDP (a framework for modeling the decision-making process) have been labeled as almost non-existent. This major gap in the prevalence of these techniques calls for extra research in the future.

C. Recommendations for Future Research

Our research offers a number of fresh perspectives on the use of AI in SCM. First of all, it highlights several SCM subfields that have not received much attention yet have a lot of potential for AI-driven innovation, like green supply chains, healthcare logistics, and logistics risk management. Second, our findings emphasize the necessity of a more comprehensive strategy that takes into account the intricate, multidimensional structure of SCM in addition to going beyond one-way linkages. Furthermore, we highlight the unrealized potential of AI in SCM to improve forecasting, sales, and costs—aspects that have gotten less attention than production and inventory planning. By filling in these gaps, our work highlights the significance of AI in improving SCM sustainability and efficiency and provides a path forward for further research and real-world applications.

To guarantee the ongoing development and internationalization of AI applications in SCM and to encourage scholars and practitioners to participate in this dynamic subject, it is essential to fill these research gaps.

Our study identifies important topics for further investigation and provides numerous crucial insights into the use of AI in SCM. First and foremost, in order to address current disparities, international and cross-institutional cooperation in AI research for SCM needs to be prioritized. Empirical research in developing countries with quickly developing economies is one area in particular that needs attention. Second, even though AI has improved many SCM subfields, including inventory planning, supplier selection, and manufacturing, a more comprehensive study is still needed to fully understand how these factors are interconnected. Understudied fields like costs, sales, forecasts, logistics hub management, healthcare logistics, and green supply chain management should receive special attention in future studies. Finally, our research indicates a sizable gap in the use of cutting-edge AI methods in supply chain management, including robotics, natural language processing, knowledge representation, and Markov decision processes. To realize the full potential of AI, researchers ought to give priority to these techniques. To advance AI applications in SCM and improve global integration, efficiency, and sustainability, these gaps must be filled.

V. Conclusions

This study evaluated 140 notable contributions to SCM AI applications during the previous 20 years using a three-step assessment process. Our analysis included citation numbers, journal placements, and publication years to present a thorough picture of the state of research. We identified top journals and contributing nations, plotted research themes and keyword co-occurrences, and emphasized the chronological growth of AI application papers in SCM using our bibliometric study. Five main alignments and twenty-two sub-branches made up an integrated knowledge taxonomy of AI applications in SCM that was presented.

The results indicate that the chronological publication of the AI application in SC shows a fast-growing trend. The number of documents published in 2021 is five times greater than 10 years ago. International Journal of Production Research ranks, Expert Systems with Applications, International Journal of Production Economics, and Decision Support Systems, are the top four journals, which contributed with over 82.8% of all AI applications in SC papers since 1998. The US, the United Kingdom, China, France, and India are the main countries for AI applications in SC research. The co-author network analysis showed that collaboration between different research groups is limited. As a result, an active and robust global collaborative environment has yet to emerge.

The co-occurred keywords map revealed that the most frequently mentioned AI application in SC issues in each group were Artificial Intelligence & sustainable development (group 1), Supply chains & optimization (group 2), Decision support systems & supply chain management (group 3), forecasting & competition (group 4), decision support system (dds) & Scheduling (group 5). Five categories were manually used to create the knowledge taxonomy for artificial intelligence applications in SC: (i) environmental; (ii) planning and SCRM; (iii) SC fields; (iv) technologies; and (v) logistics and transportation.

It is imperative to close the noted research gaps in order to progress AI applications in SCM. We suggest that future research should focus on three areas: (i) expanding AI research to underdeveloped SCM areas; (ii) pushing for increased international research collaboration to develop thorough evaluation methodologies for AI applications in service quality; and (iii) concentrating on advanced AI techniques like Robotics, Knowledge Representation, Natural Language Processing, and Markov Decision Processes.

Our study has limitations despite these contributions. By omitting pertinent contributions from alternative formats or databases, the dependence on excellent journal articles from the Scopus database may generate bias. This issue should be addressed in future studies by utilizing a wider variety of data sources. To give stronger direction for future research, the study's suggested research gaps might also be defined more specifically. Leveraging varied knowledge and expanding AI applications in SCM requires an understanding of the obstacles to collaboration and the development of measures to encourage a unified global research environment.

To assure the ongoing advancement and globalization of AI applications in SCM, our study's conclusion emphasizes the need of filling research gaps. Researchers and practitioners may make a substantial contribution to the efficiency, sustainability, and global integration of SCM by focusing on underexplored SCM domains, prioritizing advanced AI techniques, and expanding worldwide collaboration. Filling in these research voids will encourage continued contributions from the international academic community as well as advance the area.

APPENDIX

TABLE III. TOP PUBLICATIONS IMPACTING FOR AI APPLICATIONS IN SC

Document	Year	Title	TLS	Citation	Topic Related to SC&AI
Swaminathan [23]	1998	Modeling Supply Chain Dynamics: A Multiagent Approach	628	5	Modeling Supply Chain Dynamics
Tako [24]	2012	The application of discrete event simulation and system dynamics in the logistics and supply chain context	270	4	Logistics
Dweiri [22]	2016	Designing an integrated AHP based decision support system for supplier selection in automotive industry	235	3	Supplier selection
Zimmer [25]	2016	Sustainable supplier management – a review of models supporting sustainable supplier selection, monitoring and development	224	1	Sustainable supplier management
Baryannis [26]	2019	Supply chain risk management and artificial intelligence: state of the art and future research directions	202	11	Supply chain risk management
Lezoche [27]	2020	Agri-food 4.0: A survey of the supply chains and technologies for the future agriculture	164	0	Technologies
Kanan [110]	2018	Role of multiple stakeholders and the critical success factor theory for the sustainable supplier selection process	159	1	Sustainable supplier selection
Quariguasi Frota Neto [29]	2010	From closed-loop to sustainable supply chains: the WEEE case	154	0	Sustainable supply chains
Guo [30]	2015	An RFID-based intelligent decision support system architecture for production monitoring and scheduling in a distributed manufacturing environment	148	2	RFID
Synteto [31]	2016	Supply Chain Forecasting: Theory, Practice, their Gap and the Future	132	1	Forecasting
Latha Shankar [32]	2013	Location and allocation decisions for multi-echelon supply chain network – A multi-objective evolutionary approach	119	1	Supply chain network
Dubey [33]	2020	Big data analytics and artificial intelligence pathway to operational performance under the effects of entrepreneurial orientation and environmental dynamism: A study of manufacturing organizations	116	5	Big data analytics and artificial intelligence
Giannoccaro [34]	2020	Inventory management in supply chains: a reinforcement learning approach	111	4	Inventory management
Kumar [35]	2010	Minimization of supply chain cost with embedded risk using computational intelligence approaches	105	1	Supply chain cost
Georgiadis [36]	2013	Flexible long-term capacity planning in closed-loop supply chains with remanufacturing	79	3	Closed-loop supply chains

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