Journal of Scientometric Research, 2024; 13(2):382-395.
https://www.jscires.org

Research Article

Supply Chains and Artificial Intelligence: An Approach to the State of the Art

Luis Oswaldo Rodríguez Mañay[1,*], Orlando Valencia Rodríguez[2], Jhon Antuny Pabon León[3], José Alexander Durán Pérez[3]

[1]Universidad Central Del Ecuador, ECUADOR. Facultad de Ciencias Administrativas.
[2]Universidad Nacional de Colombia, COLOMBIA. Departamento de Ingeniería Industrial – Sede Manizales. Universidad Autónoma de Manizales, COLOMBIA. Departamento de Física y Matemáticas.
[3]Universidad Francisco de Paula Santander, COLOMBIA. Departamento Ciencias Administrativas, Facultad de Ciencias Empresariales, Programa de Administración de Empresas.

ABSTRACT
The rapid advancement of Artificial Intelligence (AI) in recent years has precipitated transformative changes across various industries, with Supply Chain (SC) management being no exception. Given the swift progression and the advent of innovations such as ChatGPT, it becomes imperative to delineate both the historical and recent academic contributions to this field, thereby facilitating a comprehensive understanding of future trajectories and the potential impact of these technologies. Consequently, we conducted a scientometric review utilizing the Scopus and Web of Science databases, with data preprocessing executed via R and Python. The resultant findings are bifurcated into two sections: the first encompasses a scientometric mapping of annual scientific production, country-specific contributions, journal publications and author collaboration analysis. The second section delineates the evolution of theoretical contributions, employing the metaphor of the Tree of Science for illustrative purposes. The conclusions underscore the paradigm-shifting impact of AI on SC management.

Keywords: Artificial Intelligence, Supply Chain, Scientometrics, Tree of Science.

Correspondence:
Luis Oswaldo Rodríguez Mañay
Universidad Central Del Ecuador, ECUADOR.
Email: lorodriguez@uce.edu.ec
ORCID: 0000-0001-7492-3148

Received: 31-05-2023;
Revised: 18-12-2023;
Accepted: 24-05-2024.

INTRODUCTION

Most global value chains today operate in volatile and turbulent environments that affect the integration of supply, production, distribution and sales. Recently, several disruptive events have complicated management, integration and operational decision-making in various industries. The effects of the post-COVID-19 pandemic, the blockage of the Suez Canal, geopolitical conflicts such as the war in Ukraine and the global shortage of microchips and semiconductors are examples of these disruptive events. As a result of this context, making correct decisions to address supply chain problems has become more difficult for managers of various companies.

The scientific community has created solutions based on the science of data analytics to address these conditions.[1,2] In this regard, extensive literature reviews have been conducted recently on the use of data analytics in supply chain management[3-6] and all of these reviews suggest that more research is needed in this expanding field. A recent literature review[4] examined 21,053 articles, including publications from six leading operations management journals since their inception and found 18 leading supply chain and operations management topics.

In their analysis, they discovered increasing areas of importance and trend encompassing (i) supply chain design, addressing issues in global supply chains, their integration, strategy, as well as political and cultural factors; (ii) supply chain management, which includes approaches such as supplier models, two-tier supply chain models, game theory-based methods, supplier inventory management and performance assessment in supply chains, as well as decisions about inventory transportation; and (iii) service operations, considering aspects such as the buyer-seller relationship, queuing theory, service quality and design, technological impact and the globalization of services, such as medical care, retail sales, among others. Another study on the influence of disruptive technologies in supply chains concluded that blockchain technology improves transparency in these chains by mitigating risks such as fraud, data loss and operational vulnerabilities, promoting trust and traceability.[7] On the other hand,[8] evaluated the effect of big data analytics projects on inter-industrial supply chains, highlighting that not

DOI: 10.5530/jscires.13.2.30

all of them are successful and providing a framework for their implementation.

Along with current advances, the interaction between digitalization and supply chain integration, in relation to business performance, has become an increasingly prominent research topic.[9] Kache and Seuring[10] in a literature review, identify various opportunities and challenges associated with the incorporation of big data analytics in the corporate and supply chain context. These include aspects such as visibility, transparency in the chain, cybersecurity, operational efficiency, capacity and technological infrastructure. For example, studies on blockchain highlight its contribution in the development of smart contracts and better collaboration by eliminating intermediaries and reducing costs.[11] The use of blockchain in logistics can considerably reduce administrative tasks by improving the visibility of transactions and eliminating processes that do not add value, benefiting the efficiency and simplification of the system.[12-14] Additionally, its application in inventory management, asset tracking and product authentication can also increase accuracy and trust among supply chain participants. Despite this, the existing literature lacks sufficient empirical studies exploring robust models and data analysis techniques.

In general, there has been an increase in the importance of using data analytical methods and quantitative models to solve relevant problems in industrial supply chains in various organizations and environments.[1] Despite the research conducted to understand the impact of Industry 4.0 technologies on supply chain performance,[15,16] more studies are needed to understand how these technologies can be implemented effectively to address the challenges of sustainable development for both businesses and society at large.[1,17,18] Furthermore, increasing unpredictability, emerging risks and constant changes represent significant challenges for modern production systems, logistics and Industry 4.0 networks. This has led to supply chains facing considerable challenges due to increased uncertainty and risks today.[19]

Publications on artificial intelligence have experienced a rapid emergence, as evidenced by the SCOPUS scientific database. In the period from 2013 to 2022, the number of publications scaled from 17,512 to 51,391, marking an almost threefold increase. However, a sustained annual growth rate of 17% has been recorded since 2018. A prime example of the application of artificial intelligence can be observed in the grocery market, particularly during the COVID-19 emergency when grocery purchases witnessed a significant upswing. To meet this demand, supermarket chains are confronted with the necessity of a redesign from a novel logistical perspective, with several strategies being proposed. Online orders can be processed in the same store, utilizing internal staff to shop during off-peak hours.[20] Another strategy could involve closing the store to customers and dedicating operations to online orders. An alternative approach could involve processing online orders from a single distribution center, using stores to fulfill orders with exceptionally fresh products and from where deliveries can be made. Online orders can be entirely managed by multiple e-hubs (an artificial intelligence solution).[21] In this context, the study objective of this research is to locate studies related to supply chain that use artificial intelligence to solve supply chain management challenges.

To achieve this objective, a query was first conducted in Scopus and Web of Science (WoS) on the topic of "Artificial Intelligence" and "Supply Chain". Subsequently, the principal articles were identified according to their position in the tree, with classic articles at the root, structural articles in the trunk and current articles in the branches. The tree-shaped visualization facilitates an understanding of the evolution of the application and the different contributions over time. It also helps identify the current perspectives of the research topic.[22]

Upon conducting the study in the period 2000-2023, several findings stand out. For instance, China emerges as the largest generator of scientific articles, with the United States producing the most cited articles.

METHODOLOGY

The present study was conducted utilizing the Scopus and Web of Science databases, which, as per Moral-Muñoz *et al.*,[23] collectively encompass approximately 150 million scholarly articles, before the removal of duplicates. The adoption of this dual-database approach is a burgeoning trend in contemporary research, designed to facilitate a more comprehensive and in-depth exploration of a given research topic.[24-26]

The integration of these databases was achieved through the use of the Tree of Science con r 'tosr' and 'bibliometrix' packages.[27,28] The search parameters for this study, including the specific keywords employed, are detailed in Table 1. These keywords span two distinct but interrelated fields: Supply Chain Management

Table 1: Parameters used in SCM and AI.

Parameters	Web of Science	Scopus
Range	2000-2023	
Date	February 9, 2023	
Document types	Papers, books, chapters, conference proceedings.	
Search field	Title, abstract and keywords	
Words	(“Supply chain” OR “logistics”) AND (change OR transformation) AND (management OR optimization). (“artificial intelligence” OR AI OR “machine learning” OR “deep learning” OR “neural networks”).	
Results	529	948
Total (Wos+Scopus)	1223	

(SCM) and Artificial Intelligence (AI) and were applied to the title, abstract and keywords of the articles. The time window shown in the Table 1 spans from the year 2000, as significant changes in logistical processes occurred from this point onward due to advances in technology and the rapid evolution of e-commerce, which facilitated the integration of the supply chain. In the review, not only papers but also books, chapters and conference proceedings are considered, as these documents also present important developments related to the investigated topic. The total number of unique articles retrieved from both databases amounted to 1,223, after the removal of 225 duplicate entries.

Figure 1 delineates the PRISMA diagram, tracing the process from the inception to the culmination of data preprocessing. The formats of WoS and Scopus databases encompass both numerical and character values, including, for instance, references. To optimize the dataset, it is imperative to implement a text mining algorithm coupled with a web scraping procedure. Notably, references in Scopus and WoS are formatted differently, necessitating their amalgamation through the separation of distinct characters and extraction of additional information such as authors and journals. The outcome of this process is an Excel file comprising 22 sheets, each containing disaggregated data for individual papers, such as the authors of the references. Subsequent steps involve partitioning the data into two segments: one for scientometric analysis and the other for the Tree of Science (ToS), commonly known as ToS by its acronym, is based on an algorithm built using R and Python software for data analysis.[28]

Scientometric Mapping

Scientific mapping constitutes a quantitative analysis methodology applied to scientific data, encompassing elements such as paper production, journal contributions, country-specific output and author productivity.[29] This process can facilitate the identification of a researcher's significance based on the citation frequency of their publications[30] which takes an approach regarding the h-index and individual h-index, or the recognition of emerging talents within a specific sub-discipline.[31] To provide a comprehensive overview of the fields of SCM and AI, we have partitioned the scientometric mapping into four distinct components: scientometric production analysis, country analysis, journal analysis and author analysis.

Tree of Science

The ToS methodology generates a citation network derived from the references of two distinct files[32] and subsequently selects the root, trunk and branch papers utilizing the SAP algorithm.[33] This algorithm has garnered substantial usage among researchers from the scientific community[34] and has been implemented across a variety of disciplines, including marketing,[35] management[36] and natural sciences.[37]

RESULTS

Scientometric Analysis

Scientific production

Scientific production allows for the identification of periods of peak productivity in a knowledge area over time. Figure 2 displays

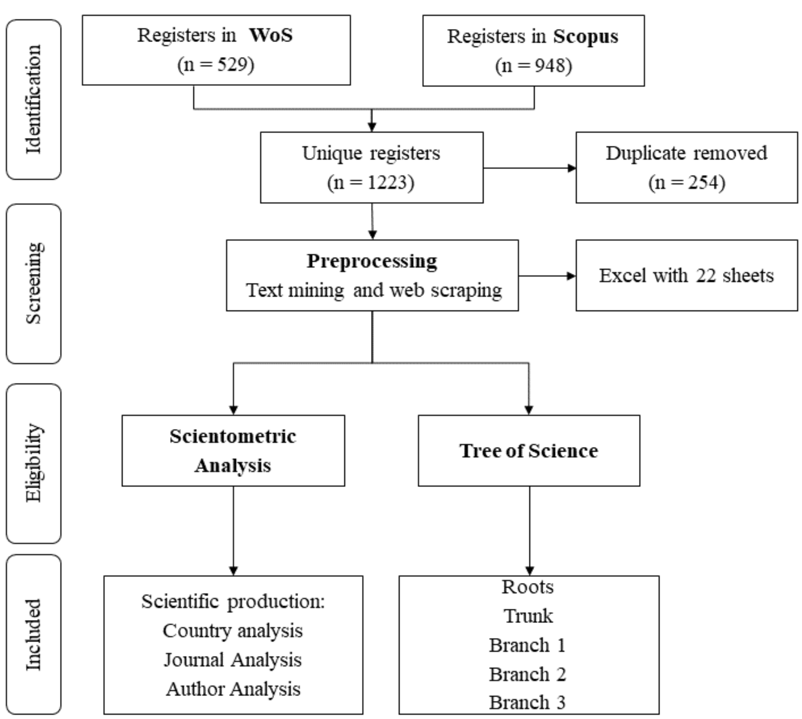

Figure 1: PRISMA diagram for preprocessing data.

the production of articles in WoS and Scopus separately for each year from 2000 to 2022. During this period, Supply Chain (SC) Management and AI experienced a total annual growth of 29.50%, signifying substantial development in this knowledge area in recent years. The following sections describe the two periods identified based on the growth of scientific production.

Onset Period (2000-2012)

The first period commences in the year 2000 and concludes in 2012. This period is characterized by a moderate growth of 23.01% (145 articles). Furthermore, the scientific production in both databases exhibits a similarity in the published articles, indicating that the articles published in Scopus are the same as those in WoS. Regarding the received citations, a total of 654 citations (combining WoS and Scopus) are recorded in 2006, with the most cited article being one that pertains to classification algorithms based on machine learning, such as the support vector machine. Factors influencing the error are identified, including the enhancement of precision, as well as the areas of application for these classification systems.[38] Similarly, in 2011, a total of 725 citations (combining WoS and Scopus) are reported. The most cited article in 2011 constitutes a literature review on methodologies employed in fire forecasting.[39]

Period of Expansion (2013-2022)

The period between 2013 and 2022 encompasses 86.96% of the total documented articles throughout the entire analyzed period (2000-2022), during which 1112 articles related to the proposed topic were published. This clearly demonstrates the exponential growth of publications (32.78%) during these years, as depicted in Figure 2. The highest level of citations was recorded in the year 2021, reaching a total of 3950. Of particular note is the most cited publication,[40] which explores the field of artificial intelligence, its notable advancements, its areas of application and the concerns surrounding the potential replacement of humans in various activities, including non-routine decision-making, in a rapid and effective manner.

Country Analysis

Table 2 displays the academic production, impact and quality of the top ten countries with the highest scientific output. The impact is determined by the number of citations, while the quality of publications is defined by the classification attained based on the ranking system utilized in the Scimago database. The classification is presented by quartiles that reflect the level of quality of the publication in such a way that a Quartile 1 (Q1) represents a higher classification level of the journal in which the corresponding article was published. Thus, the analysis of countries is based on the quality of publications.

Among the top 10 countries in scientific production, China stands out with 18.23% of the total publications found in the field of SC and AI. It is followed by the United States with 15.45%, India with 8.87% and Germany in fourth place with 4.75%. This highlights the growing significance of China in various domains, including its academic output in this field of knowledge. However, when considering impact based on the number of citations, the United States emerges as the global leader with 17.36%, followed

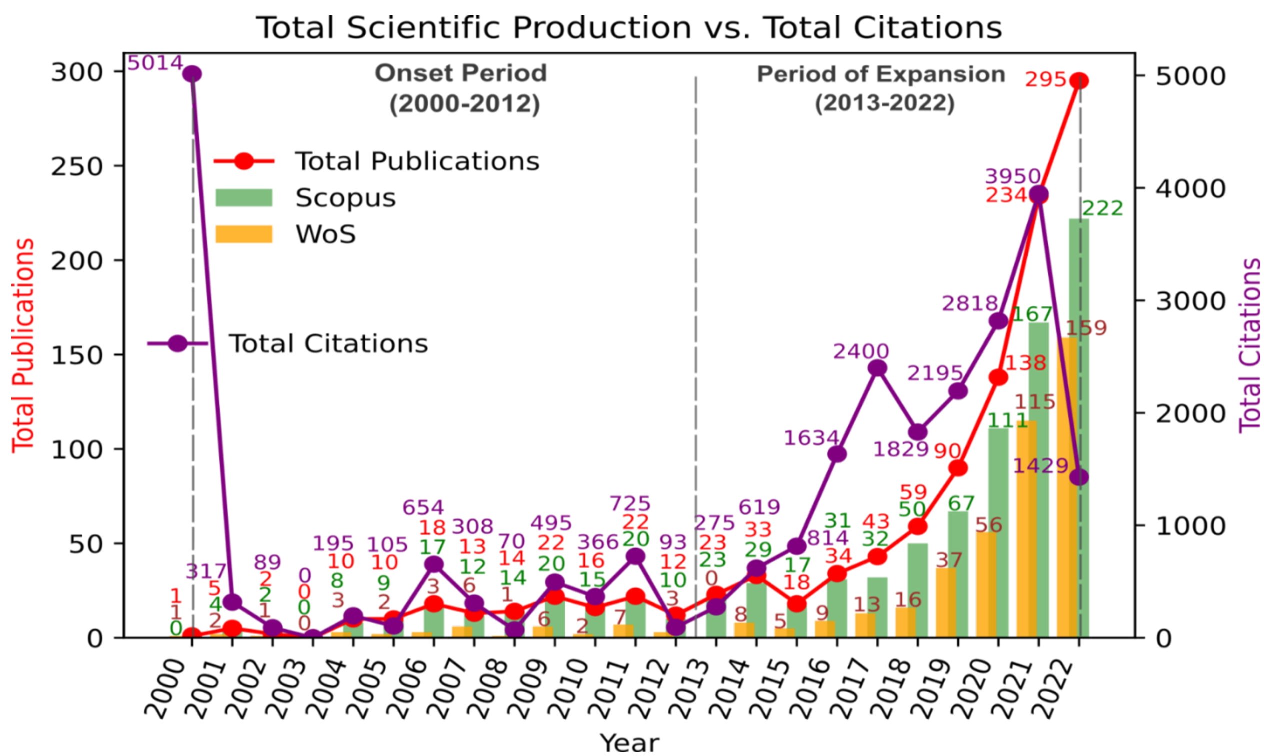

Figure 2: Annual Scientific Production.

Table 2: Top ten most productive countries.

Country	Production		Citation		Q1	Q2	Q3	Q4
China	230	18,23%	2577	9,57%	67	35	16	6
Usa	195	15,45%	4674	17,36%	99	30	4	2
India	112	8,87%	1169	4,34%	30	15	7	11
Germany	60	4,75%	620	2,30%	20	4	5	4
United Kingdom	58	4,60%	2108	7,83%	32	9	4	0
Australia	35	2,77%	1007	3,74%	16	4	2	0
Canada	34	2,69%	411	1,53%	18	1	4	1
France	32	2,54%	516	1,92%	11	5	5	0
Italy	32	2,54%	415	1,54%	10	5	4	2
Korea	32	2,54%	468	1,74%	9	7	1	1

by China with 9.57% and the United Kingdom in third place with 7.83%. Regarding the quality of publications, measured by the number of documents classified in the Q1 category, the previous ranking remains unchanged, with the United States, China and the United Kingdom occupying the top three positions.

Regarding the relationships among academic communities across countries, Figure 3 illustrates that India exhibits the highest level of interaction dynamics with more than 20 countries. However, as demonstrated in Table 2, India is ranked 3rd, indicating significant interaction with authors from numerous countries, although its publications are not at the highest academic level. Expanding on the analysis of Figure 2, it is evident that the United States also demonstrates intensive academic relationships with a significant number of countries, prominently including China, Australia and Canada.

One notable collaboration between the United States and China focuses on intelligent logistics based on the Internet of Things (IoT). A comprehensive review of publications on this topic from 2008 to 2019 highlights the most pertinent challenges for its development, such as the need for standardization, the establishment of protocols and concerns regarding information security, privacy and data processing. These findings underscore the imperative to further delve into the study of these aspects, which are fundamental for the advancement of Supply Chains (SC), integration of Artificial Intelligence (AI) and other technological advancements.[41]

A collaborative work involving the United States, China and Australia addresses the topic of logistics in construction project management, which incorporates Information Technologies (IT) in various project phases and throughout the project lifecycle in general.[42] Another project involving India and the United States focuses on the necessity of establishing transparent and secure supply chains that integrate new technologies, thereby enhancing their reliability.[43]

Journal Analysis

In this section, Table 3 presents the journals with the highest publication frequency on SCM and AI. Three journals are classified in quartile Q1, while only three journals are not indexed. Although "Advances in Information and Communication Technology" has a publication output of 25 articles, it is categorized in Q3. The most cited article in this journal provides a review on SCM and blockchain.[44] Another noteworthy journal is "Sustainability," which is classified in Q1 and includes 37 articles, with 23 indexed in WoS and 14 in Scopus.

Figure 4 depicts a citation network of journals. This Figure 4 showcases three thematic clusters, with Group 1 focusing on SCM and AI. An exemplary study within this group is the work conducted by Kim and Lee (2023), which provides a review of SCM and Customer-Customization, highlighting the impact of new technologies on these processes.[45]

Author Collaboration Network Analysis

This section presents the most prominent researchers based on their academic output in the field of artificial intelligence and supply chain. Table 4 showcases the notable productivity of authors affiliated with the United Kingdom. Among them is Professor Wang Y, recognized for his work on a blockchain-based evaluation approach for customer satisfaction in the context of urban logistics. A long-term memory machine learning algorithm was adopted to predict customer satisfaction in future periods. Its application was demonstrated through a smart contract designed to compensate or reimburse customers when their satisfaction with delivery services is low.[46]

Figure 5 displays the network of scientific collaboration among authors with extensive research contributions. A community exists around Professor Li Y and Professor Wang J, possibly due to their thematic affinity regarding Hot Spots in business management.[47]

The analysis depicted in Figure 5 provides a visualization of the scientific collaboration network among highly prolific

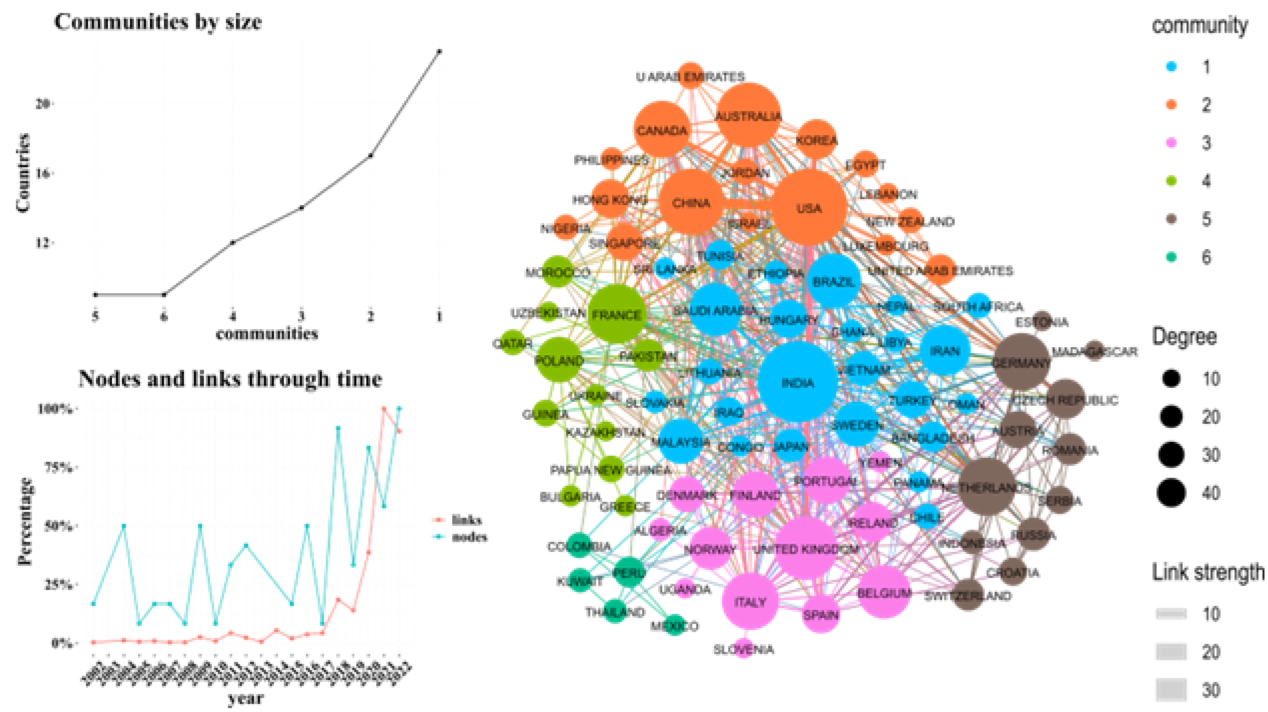

Figure 3: Country collaboration network.

Table 3: Top 10 of the most productive journal in SCM and AI.

Journal	WoS	Scopus	Impact Factor	H index	Quantile
Ifip Advances in Information and Communication Technology.	0	25	0.26	60	Q3
Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics).	0	21	-	-	-
Lecture Notes in Networks and Systems.	0	17	0.15	27	Q4
Advances In Intelligent Systems and Computing.	0	14	0	58	
Sustainability.	23	14	0.66	136	Q1
Communications in Computer and Information Science.	0	13	0,19	62	Q4
Advanced Materials Research.	0	12	0	47	-
Applied Mechanics and Materials.	0	12	0	39	-
Expert Systems with Applications.	8	10	1.87	249	Q1
International Journal of Production Research.	10	8	2.98	170	Q1

authors. While the data indicates a singular predominant cluster, suggesting a strong interconnected community, the emphasis on individual productivity may not fully exploit the analytical capabilities of the tool used. Indeed, the tool's suitability could be called into question if it merely replicates a simple count of publications without deeper network analysis. However, the additional insights into the dynamics of collaboration, as evidenced by the nodes and links through time, reveal a notable point in 2020 where the proportion of links and nodes equalizes. This equilibrium suggests a significant increase in collaborative efforts, potentially indicating a consolidation phase within the scientific community, where the creation of new connections and the fortification of existing ones occurred at a similar rate. This observation underscores the value of the network analysis by going beyond mere productivity counts to understand the evolving structure and density of scientific collaborations over time.

Tree of Science

Roots

The first article found in the roots was the contribution of the support vector machine model for data classification using the concept of feature space.[48] Later, Breiman[49] introduced the concept of "bagging," which calculates the model's result based on the sample of different data. This process improves the accuracy

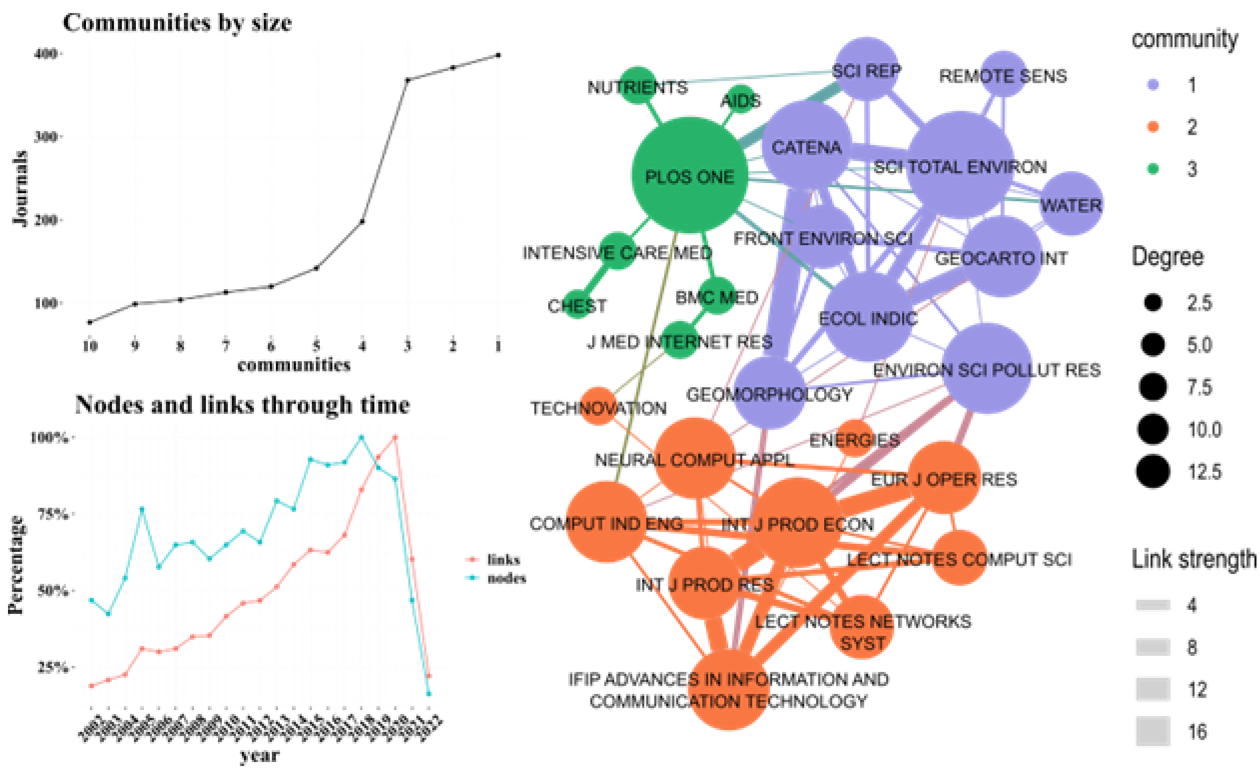

Figure 4: Citation network of journals in SCM and AI.

Table 4: Top 10 most productive authors.

No	Researcher	Total articles*	Scopsh-index	Affiliation
1	Wang Y	16	5	University Of Bedfordshire Business School, Luton, United Kingdom.
2	Wang J	12	11	Hohai University, Nanjing, China.
3	Chen Y	11	38	Stony Brook University, Stony Brook, United States.
4	Li J	10	1	Tianjin Agricultural University, Tianjin, China.
5	Li Y	10	8	The First Affiliated Hospital of Wenzhou Medical University, Wenzhou, China.
6	Liu Y	10	3	Tainan University of Technology, Tainan, Taiwan.
7	Li X	9	1	Northwest Normal University China, Lanzhou, China.
8	Liu J	9	1	Liaoning Technical University, Fuxin, China.
9	Singh R	9	30	Dr. B.R. Ambedkar National Institute of Technology, Jalandhar, India.
10	Yang X	9	5	Harbin Engineering University, Harbin, China.

of the model's results. Similarly, this same author[50] explains that two types of approaches have been used for data analysis. One is based on statistical models, which rigorously study the dataset and draw conclusions. The other is based on the use of algorithms that focus on processing large volumes of information to find characteristics and behavioral patterns. This has been facilitated by the significant increase in information processing capacity. Both perspectives are complementary for obtaining higher-quality results.

Breiman[51] analyzed the random forest learning method. It is based on different decision trees, through which independent estimations or predictions are made about the situation of interest. Then, based on each of these estimations, the global or final prediction is obtained. According to the author, better results with lower margins of error are achieved using this method.

AI has been developed to understand and mimic human behavior,[52] especially in decision-making processes. Thus, it could be employed in any business or domestic environment. In Min,[52] the author reviews the use of AI in supply chains and logistics, which has been relatively low. However, they highlight the most important areas and applications, taking into account strategic, tactical and operational decisions, as well as subfields of AI: artificial neural networks and rough set theory, machine learning, expert systems, fuzzy logic and agent-based systems. Among the

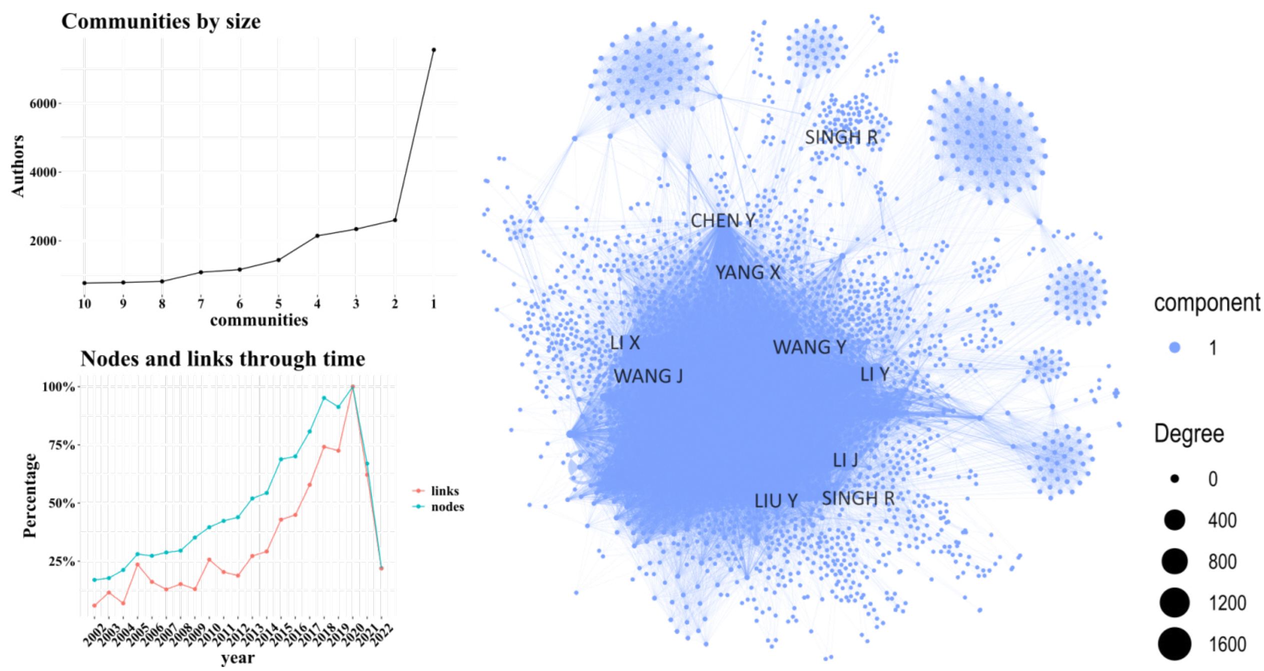

Figure 5: The personal social network of the top 10 most productive researchers.

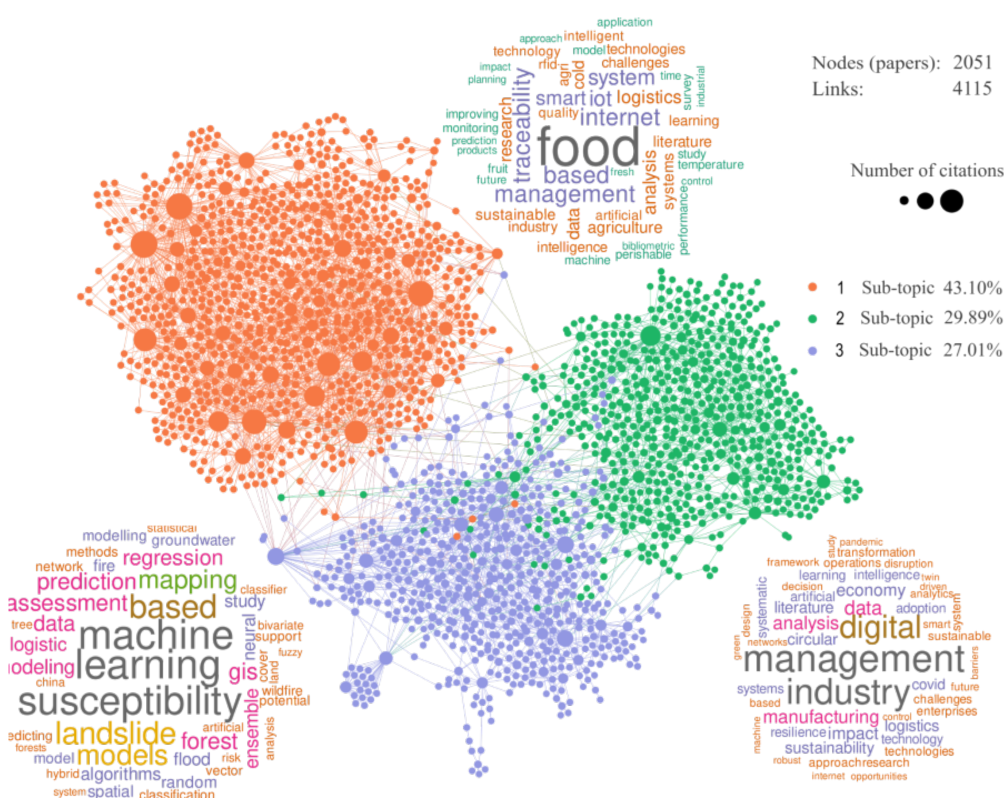

Figure 6: Citation network with the selected clusters (branches).

highlighted areas are inventory planning, transportation network design, procurement and supply management, demand planning and forecasting, order fulfillment and customer relationship management.[52]

In Chen and Guestrin,[53] the "XGBoost: A Scalable Tree Boosting System" is developed. It is a machine learning method based on decision trees that analyzes data dispersion, performs approximate learning weights and provides information on data comprehension and fragmentation to achieve more robust results.

One interesting application of AI in supply chains is risk reduction in decision-making processes, as proposed by Baryannis *et al.*[54] The author conducts a review of the types of risks and their characteristics that affect supply chains, as well as the levels of uncertainty that can arise, contributing to what is called Supply Chain Risk Management (SCRM). This application approach is complemented by Ivanov *et al.*,[55] who studies the impact of Industry 4.0 technology and its relationship with the domino effect and risks in the supply chain. Incorrect decisions can have local and global impacts that can affect all components and actors within these chains. Efforts to reduce uncertainty and minimize risks through the incorporation of Industry 4.0 technology contribute to taking timely actions to minimize impacts on supply chains.

On the other hand, Ben-Daya *et al.*[56] discuss additive manufacturing and its effects on supply chain design. This implies significant challenges as additive manufacturing involves significant changes in the use of raw materials, manufacturing times, personalized services and use of information systems. As a result, the traditional concept of the supply chain is significantly altered, as distances can be reduced and lead times shortened. However, we are still in an early stage where mass and personalized manufacturing enters into a debate about stakeholders' needs and the possibility of meeting them quickly, efficiently and cost-effectively.

Trunk

In this section of the tree, articles with applications of artificial intelligence techniques are found. For example, in one study, machine learning is applied to assist managers in understanding complex scenarios and managing inventory. An inductive learning algorithm is used to establish the most appropriate replenishment policy over time. The algorithm achieves an 88% success rate and leads to cost reduction.[57]

In subsequent research,[58] a literature review is conducted, resulting in nine value propositions that can provide a better understanding for procurement departments to analyze the benefits of implementing Industry 4.0 technologies in various activities.

Another literature review identifies the impact of new technologies on different supply chain processes.[59]

Another document identifies the contributions of machine learning techniques in supplier selection and segmentation, supply chain risk prediction, demand and sales estimation, production, inventory management, transportation and distribution, sustainable development and circular economy.[60]

A systematic review study highlights recent applications of intelligent logistics based on the Internet of Things (IoT), including smart freight transportation, storage and delivery. Current challenges include technical issues of radio-frequency identification and wireless sensor networks, limited scalability and technical capability of IoT, IoT standardization problems, IoT data acquisition and processing issues and security and privacy concerns in IoT.[41]

Another research identifies several value-creation areas for the implementation of AI in the supply chain. It also proposes an approach to design business models for AI-enabled supply chain applications.[61]

Following the arboreal metaphor for structuring the citation network, the subsequent stage focuses on the delineation of the branches, which represent distinct clusters of research activity within the field. These branches were ascertained via a citation analysis, employing the modularity optimization algorithm proposed by Blondel *et al.*,[62] which is well-suited for detecting communities within networks. This method, aligned with the approach of Zuluaga *et al.* (2014) for building citation networks, has been instrumental in identifying the three primary sub-topics within our dataset. The clusters, as depicted in Figure 6, are not merely the result of citation counts but are formed based on the strength of citation ties between papers, which is indicative of thematic affinity. This nuanced approach allows for a more sophisticated understanding of the citation landscape, highlighting the interconnectedness of research subtopics.

Branch 1. Food safety-agribusiness

One of the most recent articles related to supply chains[63] presents a very interesting approach based on inventory management. It highlights two key aspects that contribute to SC optimization: the first is the need for solid, flexible and properly managed inventories. However, these inventories must be supported by a robust forecasting system based on intensive data management, which is the second aspect emphasized by the authors. Similarly, it is indicated that both inventory and forecasting, along with other aspects of the SC, should be supported by Industry 4.0 tools and AI to ensure the flow of information required by the dynamics of these logistic processes, particularly those related to e-commerce. A proposal regarding inventory management and forecasting was also addressed by Deng and Liu,[64] but in this case, Deep Learning (DL) is utilized for forecasting. The aim is to automate the forecasting process through supervised learning using a model of this type. According to the authors, this enables faster and more efficient estimations, even achieving over 80% accuracy in demand forecasting, which can contribute to cost reduction.

On another note, Zhan and Li[65] present a study on Radio-Frequency Identification (RFID) in the SC, followed by a proposal for RFID and AI integration. The incorporation of RFID has facilitated the identification and traceability processes of goods, along with other technical elements for handling large volumes of data. By incorporating AI into SC with RFID, it was observed through experimental data analysis that response times are reduced in certain links of the logistic process compared to the original RFID-based SC. This favors the reduction of production lead time and enhances SC efficiency. Similarly, another study aimed at improving response times in supply chain networks, considering the three fundamental characteristics of Big Data (BD): high volumes of information, high velocity and high variety, is developed by Zheng *et al*.[66] AI is integrated into the SC using techniques such as genetic algorithms, ARIMA, deep learning and mixed-integer nonlinear programming.

The technique of deep learning is also employed by Joseph *et al*.[67] to forecast demand in a store. The authors propose a model that was compared with well-known techniques such as linear regression, K-Nearest Neighbors and Random Forest, yielding better results. The production and logistics processes, which may be managed by different operators, are highly interconnected and their study is essential to identify and evaluate anomalies in advance that may arise from suppliers and affect production scheduling, as well as timelines, goals and customer expectations. This is precisely what has been investigated in,[68] where the authors propose an integrated framework for production and logistics processes that employ a digitally trained twin for machine learning.

The analysis and study of supply chains have expanded across all sectors of the economy. One of these sectors is agriculture, which faces tremendous pressure due to the continuous growth of the world population and its increased demand for food. In response to these challenges, the incorporation of AI, including techniques such as machine learning, is of great importance as strategies for defining predictive processes that facilitate planning and logistics distribution,[69] with a focus on food security. A similar topic, but in this case involving one of the world's most important commodities, coffee, proposes the improvement of the supply chain through the use of big data and modern agricultural technologies, such as automated grain color classification systems, to enhance quality in harvesting and the final product.[70] Along a similar line, Smart Farming was previously proposed in,[71] defining it as a development that promotes the use of information and communication technologies, including big data and the Internet of Things, to impact not only agricultural production processes but the entire supply chain and demand forecasting components.

At the level of company production chains, the applications of artificial intelligence and the Internet of Things can be found in the so-called smart factories, within the context of Industry 4.0. One of the keys focuses has been on automating error detection to improve quality and minimize waste, rework and failures. These same principles need to be extended throughout the supply chain. However, it is not only the technical challenges that need to be overcome but also a change in mindset and cultural shift to embrace these transformations.[72]

Supply chains are part of the life of different types of businesses to enhance levels of productivity and competitiveness. In the case of food safety and agribusiness, supply chains go far beyond mere technical efficiency. It is about ensuring the production, distribution and access to food products that sustain human life. Technological advances, through data analytics, enable the identification of customer needs and preferences, estimate demand levels and make future market contracts based on predictions to ensure food security.

Branch 2. Government - industry and society

Global trends have demonstrated that government entities are not prepared to provide business stability in emergencies, exposing industries to rapid changes in their systems and processes to remain in the market.[73] The digital era has enabled organizations to automate their processes to enhance the value chain in production, utilizing data management, algorithms and vectors to predict outcomes.[74]

Advancements in data automation have led to a branch of artificial intelligence that facilitates the interpretation and analysis of societal issues based on historical data, thereby improving the achievement of sustainable development goals and providing useful tools for educational system growth.[75] Industry 4.0 presents an opportunity for industrial and creative organizations to innovate in their processes, generating new business model alternatives by utilizing artificial intelligence, the Internet of Things and blockchain, thereby delivering better products and services to customers in a shorter time and with optimal quality.[76]

Artificial intelligence enables managers to develop strategies for human resources, form better teams and anticipate process outcomes. Through the automation of learning and analysis of key components, supportive decision-making models are generated, leading to enhanced managerial performance.[77]

Artificial intelligence has become an essential tool in the financial sector, allowing the identification of market trends and even predicting portfolio delinquency rates, thereby reducing placement risks in specific sectors or market niches. This enables the adjustment of requirements and portfolio service regulations in real time.[78] Additionally, AI allows for the prediction of learning models in social networks for specific groups or categories of individuals, extracting community characteristics through neural network models.[79] The industry faces significant challenges in incorporating artificial intelligence into inventory management, aiming to reduce costs and space while implementing just-in-time methods, leading to more efficient and sustainable operations.[80]

Autonomous learning is not only being used in the industrial and service sectors but also in social domains, such as environmental management, conservation and prevention. Methods exist that demonstrate correlations between harmful practices like open burning, relative humidity and air pressure, enabling the prediction of forest fires.[81] Similarly, it has been used to improve the accuracy of landslide prediction in earthquake-affected areas, providing tools for disaster prevention and reducing material and human losses.[82]

With the review made in this branch, it can be appreciated how supply chains are vital in emergency and disaster response processes, which have been exacerbated by climate changes and increased dynamics in industrial activity. Efficient disaster response, ensuring the availability and flow of resources, is essential for the rescue and transportation of injured victims and reducing the number of deaths that may occur during and after the emergency. Social logistics in the service of the community is not only promoted by governmental entities but is also part of the social responsibility of organizations. It is not just about offering products and services to our customers but contributing to the genuine development of society that enhances the well-being of citizens.

Branch 3. Sustainability, Energy and Circular Economy

The first article in Branch 3 is a literature review on the circular economy and supply chain management. Ren *et al*.[83] demonstrate a weak relationship between the circular economy and technology transfer. In Mantravadi *et al*.,[84] the problem of the lack of integration between Information Technology (IT), Operational Technology (OT) and the implementation of concepts related to the Internet of Things is discussed from an industrial perspective. They propose recommendations for the design of supply chains in the industry 4.0 environment. Similarly, the need to build smart ports is discussed, aiming to integrate information technology, the Internet of Things and artificial intelligence for optimal management and administration of logistics and production systems.[85] The authors conduct a review of 103 articles on smart ports and perform analyses that ultimately lead to proposing a framework for the transition towards smart and sustainable ports.

Another sector where logistics chains are crucial is the electricity sector, where energy supply chains are transforming to integrate various technological, communication and Internet of Things resources, leading to the incorporation of artificial intelligence systems in the sector's operations.[86] Having data and information that contribute to better operation management of the electricity sector is essential, integrating different energy sources and achieving efficient, cost-effective and sustainable redistribution. In the same vein, Viskovic *et al*.[87] highlight the need to consolidate the incorporation of artificial intelligence in the new energy supply chain system, even as there is a decentralization of different energy sources, making it more complex to manage an integrating system for this sector. The importance of AI in efficient energy management is also demonstrated in Ahmad *et al*.,[88] consider fuzzy logic, artificial neural networks, genetic algorithms and expert systems as powerful techniques. The advantages of using AI compared to traditional models are shown in,[89] where various aspects such as data analysis, optimization, predictive maintenance and computational efficiency are analyzed.

In Pessot *et al*.,[90] the hyperconnectivity of the supply chain is analyzed, emphasizing the need for reliable information, secure communications and collaborative efforts beyond factory environments. The role of artificial intelligence in this Industry 4.0 revolution has significant effects on the supply chain, particularly in the realm of simulation.[91] Furthermore, Xie and Qiao[92] directly indicate that the increased computing power and implementation of computational intelligence algorithms in logistical processes and the supply chain will replace manual decision-making, resulting in more efficient and reliable outcomes. The recent pandemic has exposed the vulnerability of many companies, particularly their supply chains, which were severely impacted. Studies such as [93] analyze the repercussions of COVID-19, emphasizing resilience and sustainability as essential components in disruption management strategies, with artificial intelligence being one of the primary areas of research.

The supply chains implemented in these sectors play a crucial role in tackling the challenges our planet is facing. It is evident that the proposals put forth by various authors involve transitioning from traditional energy to alternative renewable systems and enhancing energy efficiency as an essential element of sustainability. Furthermore, the circular economy seeks to maximize resource utilization and minimize waste generation to achieve more efficient processes. In this interdependent approach, supply chains, with the integration of artificial intelligence and other technological advancements, make a significant contribution to these objectives.

CONCLUSION

The incorporation of artificial intelligence into supply chains is an opportunity to optimize the operational efficiency of businesses through better planning, less uncertain demand forecasts and estimation of more appropriate inventory levels, ultimately leading to higher profitability. Similarly, it allows greater control and visualization of the different elements interacting in the supply chain through real-time data analysis for decision-making on issues related to bottlenecks and the flow of products and processes in general.

Another interesting aspect is the ability to provide customers with a personalized experience from the moment an order is placed until its final delivery. In this way, the customer is informed about the progress of their order with real-time tracking. However, this also poses a significant ethical and legal challenge regarding the handling, custody and security of the information collected throughout all logistical processes in the supply chain. This is a crucial point to ensure the trust of customers, organizations and government entities that regulate information management.

The integration of AI in supply chains are rapidly advancing across various fields of society and requires significant economic, technological and specialized knowledge efforts for its design and implementation. However, it also necessitates other considerations, such as the need for a cultural and mindset shift to support its implementation within organizations. Important efforts are required in terms of information security, ethical commitment in data management and studies on social responsibility regarding its impact on potential human workforce substitution and plans for job relocation.

The primary AI and supply chain studies are predominantly conducted by researchers from universities in the United States, China, India and the United Kingdom. This highlights the importance of calling for Latin American researchers to also be actively involved in this line of research.

In the review and analysis carried out, it was found that China has had a significant growth in the number of publications related to SC and AI. This shows that China is beginning to consolidate as a leading actor in scientific and academic production worldwide, which is consistent with the technological, commercial and economic developments that position it, according to experts, as the second power on the planet, very close to the United States.

The SC is vital in the operation of any organization, to such an extent that it becomes the structural part of the logistics system, not only of the company but also of the sector within which it interacts, locally and with a global scope, such as This is especially the case with multinationals, where much of the success of their operation is found in the economy and efficiency of the SC. This is how the incorporation of the tools and technologies of Industries 4.0 and artificial intelligence is no longer discussed its need and importance, but how it should be implemented, what strategies should be used and what are the most appropriate alternatives to achieve Effective and reliable CS, which supports the production and distribution apparatus of goods and services.

ACKNOWLEDGEMENT

Authors acknowledge the universities Universidad Central del Ecuador, Universidad Nacional de Colombia, Universidad Autónoma de Manizales y Universidad Francisco de Paula Santander, for giving us the opportunity to conduct research for the scientific and academic community and to researcher Sebastián Robledo from Core of Science.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interest.

ABBREVIATIONS

WoS: Web of Science; **AI:** Artificial Intelligence; **SC:** Supply Chain; **TOS:** Tree of Science; **SCM:** Supply Chain Management.

REFERENCES

1. Kumar D, Singh RK, Mishra R, Vlachos I. Big data analytics in supply chain decarbonisation: a systematic literature review and future research directions. International Journal of Production Research. 2023;62(4):1489-1509. doi:10.1 080/00207543.2023.2179346.
2. Riahi Y, Saikouk T, Gunasekaran A, Badraoui I. Artificial intelligence applications in supply chain: A descriptive bibliometric analysis and future research directions. Expert Systems with Applications. 2021; 173:114702. doi: 10.1016/j.eswa.2021.114702.
3. Maheshwari S, Gautam P, Jaggi CK. Role of Big Data Analytics in supply chain management: current trends and future perspectives. In International Journal of Production Research. 2021;59(6):1875-1890. doi: 10.1080/00207543.2020.1793011.
4. Manikas A, Boyd L, Guan J, Hoskins K. A review of operations management literature: a data-driven approach. International Journal of Production Research. 2020;58(5):1442-1461. doi: 10.1080/00207543.2019.1651459.
5. Nguyen T, Zhou L, Spiegler V, Ieromonachou P, Lin Y. Big data analytics in supply chain management: A state-of-the-art literature review. Computers and Operations Research. 2018; 98:254-264. doi: 10.1016/j.cor.2017.07.004.
6. Wang G, Gunasekaran A, Ngai E W T, Papadopoulos T. Big data analytics in logistics and supply chain management: Certain investigations for research and applications. International Journal of Production Economics. 2016; 176:98-110. doi: 10.1016/j.ijpe.2016.03.014.
7. Alkhudary R, Queiroz MM, Féniès P. Mitigating the risk of specific supply chain disruptions through blockchain technology. Supply Chain Forum. 2022;25(1):1-11. doi: 10.1080/16258312.2022.2090273.
8. Queiroz M M, Telles R. Big data analytics in supply chain and logistics: an empirical approach. International Journal of Logistics Management. 2018;29(2):767-83. doi: 10.1108/IJLM-05-2017-0116.
9. Liu KP, Chiu W. Supply Chain 4.0: the impact of supply chain digitalization and integration on firm performance. Asian Journal of Business Ethics. 2021;10(2):371-89. doi: 10.1007/s13520-021-00137-8.
10. Kache F, Seuring S. Challenges and opportunities of digital information at the intersection of Big Data Analytics and supply chain management. International Journal of Operations and Production Management. 2017;37(1):10-36. doi:10. 1108/IJOPM-02-2015-0078.
11. Pratap S, Jauhar S K, Gunasekaran A, and Kamble S S. Optimizing the IoT and big data embedded smart supply chains for sustainable performance. In Computers and Industrial Engineering. 2024; 187:109828. doi: 10.1016/j.cie.202 3.109828.
12. Adams R, Parry G, Godsiff P, Ward P. The future of money and further applications of the blockchain. Strategic Change. 2017;26(5):417-422. doi: 10.1002/jsc.2141.
13. Seidel M D L. Questioning Centralized Organizations in a Time of Distributed Trust. Journal of Management Inquiry. 2018;27(1):40-44. doi: 10.1177/10564926 17734942.
14. Shermin V. Disrupting governance with blockchains and smart contracts. Strategic Change. 2017;26(5):499-509. doi: 10.1002/jsc.2150.
15. Arji G, Ahmadi H, Avazpoor P, Hemmat M. Identifying resilience strategies for disruption management in the healthcare supply chain during COVID-19 by digital innovations: A systematic literature review. Informatics in Medicine Unlocked. 2023; 38:101199. doi: 10.1016/j.imu.2023.101199.
16. Rad F F, Oghazi P, Palmié M, Chirumalla K, Pashkevich N, Patel P C, *et al*. Industry 4.0 and supply chain performance: A systematic literature review of the benefits, challenges and critical success factors of 11 core technologies. Industrial Marketing Management. 2011; 105:268-93. doi: 10.1016/j.indmarman.2022.06.009.
17. Shet S V, Pereira V. Proposed managerial competencies for Industry 4.0 - Implications for social sustainability. Technological Forecasting and Social Change. 2021; 173:121080. doi: 10.1016/j.techfore.2021.121080.
18. Taddei E, Sassanelli C, Rosa P, Terzi S. Circular supply chains in the era of industry 4.0: A systematic literature review. Computers and Industrial Engineering. 2022; 170:108268. doi: 10.1016/j.cie.2022.108268.
19. Ivanov D, Sethi S, Dolgui A, Sokolov B. A survey on control theory applications to operational systems, supply chain management and Industry 4.0. Annual Reviews in Control. 2018;46: 134-147. doi: 10.1016/j.arcontr ol.2018.10.014.
20. El Bhilat E M, El Jaouhari A, and Hamidi L S. Assessing the influence of artificial intelligence on agri-food supply chain performance: the mediating effect of distribution network efficiency. Technological Forecasting and Social Change. 2024; 200:123149. doi: 10.1016/j.techfore.2023.123149.
21. Calzavara M, Finco S, Persona A, Zennaro I. A cost-based tool for the comparison of different e-grocery supply chain strategies. Int JProd Econ. 2023;262(108899):108899.
22. Grisales A M, Robledo S, Zuluaga M. Topic Modeling: Perspectives from a Literature Review. IEEE Access. 2023; 11:4066-4078. doi: 10.1109/ACCESS.2022.3232939.
23. Moral-Muñoz JA, Herrera-Viedma E, Santisteban-Espejo A, Cobo MJ. Software tools for conducting bibliometric analysis in science: An up-to-date review. El Profesional de la información. 2020;29(1): e290103. doi: 10.3145/epi.2020.ene.03.
24. Serra F A R, Ferreira M P, Guerrazzi L A D C, Scaciotta V V. Doing bibliometric reviews for the Iberoamerican Journal of Strategic Management. Iberoamerican Journal of Strategic Management. 2018;17(03):1-16.
25. Botero CM, Milanes CB, Robledo S. 50 years of the Coastal Zone Management Act: The bibliometric influence of the first coastal management law on the world. Mar Policy. 2023; 150:105548. doi: 10.1016/j.marpol.2023.105548.
26. Lisena P, Harrando I, Kandakji O, and Troncy R. TOMODAPI: A topic modeling API to train, use and compare topic models. NLP-OSS. 2020:132-140.
27. Aria M, Cuccurullo C. bibliometrix: An R-tool for comprehensive science mapping analysis. J Informetr. 2017;11(4):959-75.

28. Zuluaga M, Robledo S, Arbelaez-Echeverri O, Osorio-Zuluaga GA, Duque-Méndez N. Tree of Science - ToS: A web-based tool for scientific literature recommendation. Sci Technol Libr. 2022;(100). doi: 10.29173/istl2696.
29. Robledo S, Duque P, Aguirre AMG. Word of Mouth Marketing: A Scientometric Analysis. J Sci Res Chulalongkorn Univ. 2023;11(3):436-446.
30. Bi HH. Four problems of the h-index for assessing the research productivity and impact of individual authors. Scientometrics. 2023;128:2677-2691. doi: 10.1007/s11192-022-04323-8
31. Haunschild R, Bornmann L. Identification of potential young talented individuals in the natural and life sciences: A bibliometric approach. J Informetr. 2023;17(3):101394.
32. Robledo S, Zuluaga M, Valencia-Hernandez LA, Arbelaez-Echeverri OAE, Duque P, Alzate-Cardona JD. Tree of Science with Scopus: A Shiny application. Issu Sci Technol Libr. 2022;(100). doi: 10.29173/istl2698.
33. Valencia-Hernandez DS, Robledo S, Pinilla R, Duque-Méndez ND, Olivar-Tost G. SAP algorithm for citation analysis: An improvement to tree of science. Ingeniería e Investigación. 2020;40(1). doi: 10.15446/ing.investig.v40n1.7718.
34. Eggers F, Risselada H, Niemand T, Robledo S. Referral campaigns for software startups: The impact of network characteristics on product adoption. J Bus Res. 2022; 145:309-24.
35. Barrera Rodríguez AM, Duque Oliva EJ, Vieira Salazar JA. Actor engagement: origin, evolution and trends. J Bus Ind Mark. 2023;38(7):1479-1497.
36. Hoyos O, Castro Duque M, Toro León N, Trejos Salazar D, Montoya-Restrepo LA, Montoya-Restrepo IA, *et al*. Gobierno corporativo y desarrollo sostenible: un análisis bibliométrico. Rev, CEA. 2023;9(19): e2190.
37. Aguirre KA, Paredes Cuervo D. Water safety and water governance: A scientometric review. Sustain Sci Pract Policy. 2023;15(9):7164.
38. Bartlett PL, Jordan MI, McAuliffe JD. Convexity, classification and risk bounds. J Am Stat Assoc. 2006;101(473):138-156.
39. Thompson MP, Calkin DE. Uncertainty and risk in wildland fire management: a review. J Environ Manage. 2011;92(8):1895-1909.
40. Dwivedi YK, Hughes L, Ismagilova E, Aarts G, Coombs C, Crick T, *et al*. Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities and agenda for research, practice and policy. Int J Inf Manage. 2021;57(101994):101994.
41. Ding Y, Jin M, Li S, Feng D. Smart logistics based on the internet of things technology: an overview. Int J Logist Res Appl. 2021;24(4):323-345.
42. Huang Y, Shi Q, Zuo J, Pena-Mora F, Chen J. Research status and challenges of data-driven construction project management in the Big Data context. Adv Civ Eng. 2021; 2021:1-19.
43. Hassija V, Chamola V, Gupta V, Jain S, Guizani N. A survey on supply chain security: Application areas, security threats and solution architectures. IEEE Internet Things J. 2021;8(8):6222-6246.
44. Demertzis K, Iliadis L, Pimenidis E, Tziritas N, Koziri M, Kikiras P, *et al*. Federated blockchained supply chain management: A CyberSecurity and privacy framework. IFIP Advances in Information and Communication Technology. Cham: Springer. 2021;627: 769-79. doi: 10.1007/978-3-030-79150-6_60
45. Kim S, Lee K. The paradigm shift of mass customisation research. Int J Prod Res. 2022;61(10):3350-3376. doi: 10.1080/00207543.2022.2081629.
46. 46. Tian Z, Zhong RY, Vatankhah Barenji A, Wang YT, Li Z, Rong Y. A blockchain-based evaluation approach for customer delivery satisfaction in sustainable urban logistics. Int J Prod Res. 2020;59(7):2229-2249. doi: 10.1080/00207543.2020.1809733.
47. Wang Y, Chi X, Liu M. Visual analysis of the development and hot spots of Chinese enterprises' management. 2020 International Conference on Virtual Reality and Visualization (ICVRV). 2020;107-112. doi: 10.1109/ICVRV51359.2020.00031.
48. Cortes C, Vapnik V. Support-vector networks. Mach Learn. 1995;20(3):273-297.
49. Breiman L. Bagging predictors. Machine Learning. 1996;24(2):123-140.
50. Breiman L. Statistical Modeling: The Two Cultures (with comments and a rejoinder by the author). Stat Sci. 2001;16(3):199-231.
51. Breiman L. Random Forests. Machine Learning; 2001;45(1):5-32.
52. Min H. Artificial intelligence in supply chain management: theory and applications. Int J Logist Res Appl. 2010;13(1):13-39.
53. Chen T, Guestrin C. XGBoost: A scalable tree boosting system. Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining. 2016:785-794. doi: 10.1145/2939672.2939785.
54. Baryannis G, Validi S, Dani S, Antoniou G. Supply chain risk management and artificial intelligence: state of the art and future research directions. Int J Prod Res. 2018;57(7):2179-2202.
55. Ivanov D, Dolgui A, Sokolov B. The impact of digital technology and Industry 4.0 on the ripple effect and supply chain risk analytics. Int J Prod Res. 2019;57(3):829-846.
56. Ben-Daya M, Hassini E, Bahroun Z. Internet of things and supply chain management: a literature review. Int J Prod Res. 2019;57(15-16):4719-4742.
57. Priore P, Ponte B, Rosillo R, de la Fuente D. Applying machine learning to the dynamic selection of replenishment policies in fast-changing supply chain environments. Int J Prod Res. 2019;57(11):3663-3677.
58. Jahani N, Sepehri A, Vandchali HR, Tirkolaee EB. Application of Industry 4.0 in the Procurement Processes of Supply Chains: A Systematic Literature Review. Sustain Sci Pract Policy. 2021;13(14):7520.
59. Zekhnini K, Cherrafi A, Bouhaddou I, Benghabrit Y, Garza-Reyes JA. Supply chain management 4.0: a literature review and research framework. Benchmarking: An International Journal. 2020;28(2):465-501.
60. Tirkolaee EB, Sadeghi S, Mooseloo FM, Vandchali HR, Aeini S. Application of Machine Learning in Supply Chain Management: A Comprehensive Overview of the Main Areas. Math Probl Eng. 2021; 1:1476043. doi: 10.1155/2021/1476043.
61. Helo P, Hao Y. Artificial intelligence in operations management and supply chain management: an exploratory case study. Prod Plan Control. 33; 16:1573-1590. doi: 10.1080/09537 287.2021.1882690.
62. Blondel VD, Guillaume JL, Lambiotte R, Lefebvre E. Fast unfolding of communities in large networks. Journal of statiscal mechanics. 2008;10: P10008. doi: 10.1088/ 1742-5468/2008/10/P10008.
63. Tang YM, Chau KY, Lau YY, Zheng Z. Data-intensive inventory forecasting with artificial intelligence models for cross-border E-commerce service automation. Appl Sci. 2023;13(5):3051.
64. Deng C, LiuY. A deep learning-based inventory management and demand prediction optimization method for anomaly detection. Proc Int Wirel Commun Mob Comput Conf. 2021;1(9969357):1-14.
65. Zhang H, Li Z. RFID supply chain data deconstruction method based on artificial intelligence technology. Open Computer Science. 2023;13(1):20220265. doi: 10.1515/comp-2022-0265.
66. Zheng J, Alzaman C, Diabat A. Big data analytics in flexible supply chain networks. Comput Ind Eng. 2023; 178:109098.
67. Joseph RV, Mohanty A, Tyagi S, Mishra S, Satapathy SK, Mohanty SN. A hybrid deep learning framework with CNN and Bi-directional LSTM for store item demand forecasting. Comput Electr Eng. 2022; 103:108358.
68. Greis NP, Nogueira ML, Rohde W. Digital twin framework for machine learning-enabled integrated production and logistics processes. IFIP Advances in information and Communication Technology. 2021;630: 218-227. doi: 10.1007/978-3-030-85874-2_23.
69. Ben Ayed R, Hanana M. Artificial intelligence to improve the food and agriculture sector. Journal of Food Quality. 2021; 1:5584754.
70. Kittichotsatsawat Y, Jangkrajarng V, Tippayawong KY. Enhancing coffee supply chain towards sustainable growth with big data and modern agricultural technologies. Sustain Sci Pract Policy. 2021;13(8):4593.
71. Wolfert S, Ge L, Verdouw C, Bogaardt MJ. Big Data in Smart Farming - A review. Agric Syst. 2017; 153:69-80.
72. Canciglierie AB, da Rocha T, Szejka AL, dos Santos Coelho L, Junior OC. Real-time machine learning automation applied to failure prediction in automakers supplier manufacturing system. IFIP Advances in information and Communication Technology. 2021;630: 303-310. doi: 10.1007/978-3-030-85874-2_32.
73. Khan MA, Segovia JET, Bhatti MI, Kabir A. Corporate vulnerability in the US and China during COVID-19: A machine learning approach. Journal Economic Asymmetries. 2023;27: e00302. doi: 10.1016/j.eca. 2023.e00302.
74. Nguyen HS, Huynh CD, Bui NQ. Digital transformation for shippingcontainer terminals using automated container code recognition. TELKOMNIKA. 2023;21(3):535.
75. Zhou X, Luo Z, Wang H, Luo Y, Yu R, Zhou S, *et al*. Machine learning application in forecasting tire wear particles emission in China under different potential socioeconomic and climate scenarios with tire microplastics context. Journal of Hazardous Materials. 2023; 441:129878. doi: 10.1016/j.jhazmat.2022.129878.
76. Qu M. Research on digital transformation in cultural and creative industries to realize industry 4.0. Proceedings of the 2021 3rd International Conference on E-Business and E-commerce Engineering. 2021: 79-83. doi: 10.1145/3510249.3510264.
77. Mourad Z, Noura A, Mohamed C. Towards a new method for classifying employee performance using machine learning algorithms. International Conference on Intelligent Systems and Computer Vision (ISCV). 2022: 1-5.
78. Fraisse H, Laporte M. Return on investment on artificial intelligence: The case of bank capital requirement. J Bank Financ. 2022; 138:106401.
79. Rajita BSAS, Tarigopula P, Ramineni P, Sharma A, Panda S. Application of evolutionary algorithms in social networks: A comparative machine learning perspective. New Gener Comput. 2023;41(2):401-44.
80. Eldred ME, Thatcher J, Rehman A, Gee I, Suboyin A. Leveraging AI for Inventory Management and Accurate Forecast - An Industrial Field Study. SPE Middle East Intelligent Oil and Gas Symposium. 2023; D011S001R001.
81. Bai B, Zhao H, Zhang S, Li X, Zhang X, Xiu A. Forecasting Crop Residue Fires in Northeastern China Using Machine Learning. Atmosphere. 2022;13(10):1616.
82. Wang S, Lin X, Qi X, Li H, Yang J. Landslide susceptibility analysis based on a PSO-DBN prediction model in an earthquake-stricken area. Front Environ Sci Eng China. 2022;10. doi: 10.3389/fenvs.2022.912523.
83. Ren Y, Li R, Wu KJ, Tseng ML. Discovering the systematic interlinkages among the circular economy, supply chain, industry 4.0 and technology transfer: A bibliometric analysis. Cleaner and Responsible Consumption. 2023; 9:100123.
84. Mantravadi S, Srai JS, Møller C. Application of MES/MOM for Industry 4.0 supply chains: A cross-case analysis. Comput Ind. 2023; 148:103907.
85. Liao HT, Lo TM, Pan CL. Knowledge mapping analysis of intelligent ports: Research facing global value chain challenges. Systems. 2023;11(2):88.
86. Franki V, Majnarić D, Višković A. A comprehensive review of Artificial Intelligence (AI) companies in the power sector. Energies. 2023;16(3):1077.
87. Viskovic A, Franki V, Jevtic D. Artificial intelligence as a facilitator of the energy transition [Internet]. 2022 45th Jubilee International Convention on Information, Communication and Electronic Technology (MIPRO). 2022:494-499. doi:10.23919/MIPRO55190.2022.9803700.
88. Ahmad T, Zhu H, Zhang D, Tariq R, Bassam A, Ullah F, *et al*. Energetics Systems and artificial intelligence: Applications of industry 4.0. Energy Rep. 2022; 8:334-61.
89. Ahmad T, Zhang D, Huang C, Zhang H, Dai N, Song Y, *et al*. Artificial intelligence in sustainable energy industry: Status Quo, challenges and opportunities. Journal of Cleaner Production. 2021; 289:125834. doi: 10.1016/j.clepro.2021.125834.
90. Pessot E, Zangiacomi A, Fornasiero R. Unboxing the hyper-connected supply chain: a case study in the furniture industry. Prod Plan Control. 2022;35(6):580-598.

91. Sharifpour H, Ghaseminezhad Y, Hashemi-Tabatabaei M, Amiri M. Investigating cause-and-effect relationships between supply chain 4.0 technologies. Eng Manag Prod Serv. 2022;14(4):22-46.
92. Xie ME, Qiao L. Exploring the application of computer intelligence algorithms in logistics and supply chain management. Proceedings of the 7th International Conference on Intelligent Information Processing. 2022:1-7. doi: 10.1145/3570236.3570257.
93. Moosavi J, Fathollahi-Fard AM, Dulebenets MA. Supply chain disruption during the COVID-19 pandemic: Recognizing potential disruption management strategies. Int J Disaster Risk Reduct. 2022; 75:102983.

Cite this article: Rodríguez – Mañay L, Valencia – Rodríguez O, Pabon - León J y Durán - Pérez J. Supply Chains and Artificial Intelligence: An Approach to the State of the Art. J Scientometric Res. 2024;13(2):382-95.