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Department of Business Administration

BIBLIOMETRIC ANALYSIS OF THE IMPACT OF ARTIFICIAL INTELLIGENCE ON SUPPLY CHAIN MANAGEMENT

Master Thesis

Farid Ahmad JALALI

Supervisor

Assoc. Prof. Dr. Çağla TUĞBERK ARIKER

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Turkish Abstract

Bu tez, Scopus veri tabanından elde edilen verilere dayanarak, Yapay Zekâ'nın (YZ) Tedarik Zinciri Yönetimi (TZY) üzerindeki etkisini bibliyometrik bir analizle incelemektedir. Çalışma, 2020 ile 2024 yılının ilk çeyreği arasındaki araştırma yayınlarını kapsamakta olup, özellikle YZ'nin lojistik ve envanter yönetimindeki uygulamalarına odaklanmaktadır. Araştırma, TZY'de YZ entegrasyonunun giderek büyüyen kapsamını açıklamayı, yayın eğilimleri, coğrafi dağılım, önde gelen dergiler, konferanslar, ortaya çıkan konular ile etkili makaleler, yazarlar ve kurumların atıf analizlerini detaylı bir şekilde incelemeyi amaçlamaktadır.

Sonuçlar, bu alandaki araştırma faaliyetlerinde ve yayınlarda kayda değer bir artış olduğunu göstermekte ve Yapay Zekâ'nın (YZ) Tedarik Zinciri Yönetimini (TZY) geliştirmedeki artan ilgisini ve önemini vurgulamaktadır. Ana bulgular, Makine Öğrenimi (MÖ), Derin Öğrenme (DÖ) ve üretken zıt ağlar gibi YZ tabanlı teknolojilerin verimlilik, öngörüsel analizler, otomasyon ve tedarik zinciri görünürlüğü sağladığını ortaya koymaktadır. Ayrıca, sürdürülebilir akıllı şehirler, gıda israfı yönetiminde keşifsel çalışmalar ve tersine lojistik gibi öncü kümelemeler tespit edilmiştir. Bu durum, YZ'nın TZY'deki çeşitli uygulamalarını ve faydalarını göstermektedir.

Scopus Veri Tabanının tek bilgi kaynağı olarak seçilmesi, ilgili yayınların sayısını sınırlamakta ve diğer veri tabanlarında listelenen ilgili çalışmaları dışlamaktadır. Benzer durumlar, çalışma alanına parçalı bir bakış açısı sunmaktadır. Yine de bu çalışma, araştırmacılar, politika yapıcılar ve uygulayıcılar için değerli bilgiler sunmaktadır. Ayrıca, gelecekteki araştırma yönlerini belirlemelerine ve YZ ile TZY alanlarında yatırım yapılması gereken noktaları vurgulamalarına yardımcı olmaktadır.

Çalışma, yalnızca mevcut akademik yayınlara odaklanarak YZ sistemlerinin yeteneklerini, avantajlarını ve TZY alanındaki genel etkilerini ortaya koymaktadır. Ayrıca, YZ tabanlı teknolojilerin yorumlanmasını ve bunların TZY'ye uygulanmasını vurgulamaktadır. Bu, YZ'nın bilinçli karar alma, ileri teknoloji dönüşümü ve ideal iş birliği ile sonuçlar üzerindeki etkisine dair bilgiler sunmaktadır. Buna ek olarak, ilgili konular üzerine daha fazla analiz yapılması gerektiği belirtilmektedir. Yazar,

YZ'nın yenilikçi yeteneklerinin tam entegrasyonunun ve TZY alanındaki kullanımının, akademisyenler ve uygulayıcıların iş birliği ve ortak çalışmalarıyla sağlanacağına inanmaktadır.

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Istanbul – 2025

DECLARATION

I hereby declare that scientific and ethical rules have been followed in preparing this thesis, the works of other persons have been referenced in accordance with scientific norms if used, there is no falsification in the used data, and any part of the thesis has not been submitted to this university or any other university as another thesis.

Farid Ahmad JALALI
...…./……/2025

TO ISTANBUL GELISIM UNIVERSITY
THE DIRECTORATE OF THE INSTITUTE OF GRADUATE STUDIES

The thesis study of FARDI AHMAD JALALI titled A Bibliometric Analysis of the Impact of Artificial Intelligence on Supply Chain Management has been accepted as MASTER THESIS in the Department of Business Administration by our jury.

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Member — *Assoc. Prof. Çağla Tuğberk ARIKER* (Supervisor)

Member — *Asst. Prof. Dr. Birol BAYSAK*

APPROVAL

I approve that the signatures above belong to the aforementioned faculty members.

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Prof. Dr. İzzet GÜMÜŞ

Director of the Institute

SUMMARY

This thesis presents a bibliometric analysis of the impact of Artificial Intelligence (AI) on Supply Chain Management (SCM) based on data extracted from the Scopus database. The study covers research publications from 2020 to the first quarter of 2024, with a particular focus on the applications of AI in logistics and inventory management. This research aims to explain the growing landscape of AI integration in SCM by a detailed examination of publication trends, geographical distribution, emerging topics, and citation analysis of influential papers, authors, and institutions.

The results demonstrate a notable increase in research activity and publications in this field, highlighting AI's growing interest and importance in enhancing SCM. Key findings point out that AI-based technologies like Machine Learning (ML), Deep Learning (DL), and generative adversarial networks create efficiency, predictive analytics, automation, and supply chain visibility. Moreover, the analysis recognizes a number of leading clusters, including sustainable smart cities, exploratory studies in food waste management, and reverse logistics. It shows AI's diverse applications and benefits in SCM.

The Scopus Database's selection as a single source of information limits the number of relevant publications and excludes relevant studies listed in other databases. Similar cases display a fragmentary view of the study landscape. Still, the study offers valuable knowledge for researchers, policymakers, and practitioners. In addition, it helps them determine future research directions and underscores areas for investment in AI and SCM.

The study exclusively focuses on the existing academic publications to reveal AI systems' capacities, advantages, and overall impact on the SCM domain. In addition, it underlines the interpretation of AI-based technologies and their implementation into SCM. It gives knowledge regarding AI's impact on informed decision-making, advanced technology transformation, and ideal collaboration and outcomes. Moreover, the need for further analysis of related topics is highlighted. The author has faith in collaboration and teamwork by scholars and practitioners. Their

joint work ensures the complete integration of AI's innovative capabilities and their usage in the SCM domain.

Key Words: Artificial Intelligence, Supply Chain Management, Logistics, Inventory Management.

ÖZET

Bu tez, Scopus veri tabanından elde edilen verilere dayanarak, Yapay Zekâ'nın (YZ) Tedarik Zinciri Yönetimi (TZY) üzerindeki etkisini bibliyometrik bir analizle incelemektedir. Çalışma, 2020 ile 2024 yılının ilk çeyreği arasındaki araştırma yayınlarını kapsamakta olup, özellikle YZ'nin lojistik ve envanter yönetimindeki uygulamalarına odaklanmaktadır. Araştırma, TZY'de YZ entegrasyonunun giderek büyüyen kapsamını açıklamayı, yayın eğilimleri, coğrafi dağılım, önde gelen dergiler, konferanslar, ortaya çıkan konular ile etkili makaleler, yazarlar ve kurumların atıf analizlerini detaylı bir şekilde incelemeyi amaçlamaktadır.

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yenilikçi yeteneklerinin tam entegrasyonunun ve TZY alanındaki kullanımının, akademisyenler ve uygulayıcıların iş birliği ve ortak çalışmalarıyla sağlanacağına inanmaktadır.

Anahtar Kelimeler: Yapay Zekâ, Tedarik Zinciri Yönetimi, Lojistik, Envanter Yönetimi

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ABBREVIATIONS

AI	**:**	Artificial Intelligence
SCM	**:**	Supply Chain Management
ML	**:**	Machine Learning
DL	**:**	Deep Learning
NLP	**:**	Natural Language Processing
IMA	**:**	Inventory Management Assistants
IıoT	**:**	Industrial Internet of Things
VRP	**:**	Vehicle Routing Problem
NLP	**:**	Natural Language Processing
RPA	**:**	Robotics Process Automation
DNN	**:**	Deep Neural Networks
RNN	**:**	Recurrent Neural Networks
ANNs	**:**	Artificial neural networks
CNN	**:**	Convolutional Neural Networks
SMEs	**:**	Small and Medium-sized Enterprises
GDPR	**:**	General Data Protection Regulation
RFID	**:**	Radio Frequency Identification Devices
DT	**:**	Digital Twins
WoS	**:**	Web of Science
TF-DF	:	Term Frequency – Inverse Document Frequency

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PREFACE

The technological advancement has been unprecedented during recent years. Artificial Intelligence (AI) and Supply Chain Management (SCM) play an important role and have been at the forefront of innovation. The impact of AI on SCM has covered numerous aspects of this domain. And this has attracted the attention of scholars and practitioners. This thesis, "Bibliometric Analysis of the Impact of Artificial Intelligence on Supply Chain Management," examines the improvements and relationships built in the evolving landscape of AI's role in supply chain management.

The motivation for this study stems from the observed fragmentation in the comprehensive understanding of AI's influence on SCM. While individual academic works have shed light on various applications during various periods, a comprehensive and quantitative overview of research trends, key contributors, and emerging themes has mainly been lacking for the last five years. The purpose of this work is to bridge the gap via a bibliometric analysis of articles and publications available in the Scopus database. This study focuses particularly on the application of AI in logistics and inventory management from the first quarter of ofa0 to the first quarter of yea4.

Through this research, we aim to offer a clear and insightful mapping of the academic discourse surrounding AI in SCM. This study identifies prominent authors, core research topics, influential institutions, and the geographical distributions of scholarly contributions. It is a worthy resource for researchers, policymakers, and practitioners. The findings of this thesis will contribute to the development of academic knowledge of managers and policymakers who are interested in the application of AI. Particularly those who use AI-based solutions to develop their supply chain performance, create resilience, and achieve sustainable growth. Such an approach is the need in today's quack-changing global economy.

This study presented considerable difficulties. However, its ultimate rewards clearly demonstrated the value of overcoming them. I present my sincere gratitude to my supervisor, Assoc. Prof. Çağla Dr. TUĞBERK ARIKER. Her invaluable guidance, unwavering support, and insightful feedback throughout this process were pivotal to the successful completion of this thesis.

I am really grateful to my family and friends for their relentless support and consideration during the tough and challenging moments. Your patience and understanding were a source of energy and strength for me.

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INTRODUCTION

Economic conditions, pandemics, developments in transportation, rapid technological change, and skillful employees are the known factors that have impacted Supply Chain Management (SCM). Artificial Intelligence (AI) has been verified to be a considerable technological development (Li & Gao, 2023) in the last few decades, transforming SCM in exceptional ways. It has taken several centuries for human beings to witness AI's transformative power. With their profound impact, AI-based technologies have already struck every aspect of business activities. According to Moor (2006), AI, pioneered by scientist John McCarthy and officially introduced at the Dartmouth conference in 1956, now plays a key role in many industries (Dhamija & Bag, 2020; Adali, 2023). Their implementation into SCM has recently obtained substantial attention. It suggests a promising future with the capability to greatly improve effectiveness, responsiveness, and competitiveness in progressively complex supply chain networks. Svoboda and Minner (2022) remarked that AI systems can support specific purposes, including inventory management (Cannas et al., 2023).

Generally, Supply chain management is key for observing the movement of products and services from origin to utilization (Helo & Hao, 2022), encompassing the process of shipping and storage of raw materials, work-in-process goods, and finished goods (Noman et al.,2022). As an indispensable component of modern business operations, SCM facilitates the seamless flow of goods and services from suppliers to end consumers. It represents the vital communication between a company and its suppliers to distribute a specific product to the final buyer (Bassiouni et al., 2024).

Neural networks, machine learning (ML), deep learning (DL), and language processing are AI-based technologies that are widely utilized in supply chains. Operational efficiency, cost reduction, informed decision-making, and increased responsiveness are their amazing capabilities (Thumar & Vaghasiya, 2024). The development is remarkable, but the research on AI's effect on SCM is fragmented. Some academic studies deliver insights into AI-SCM, but unexplored areas are still visible (Toorajipour et al., 2021).

AI is growing quickly. It requires a proportional scholarly and practical effort to keep up with achieved developments. Based on Helo and Hao 2022, the primary

evaluation of the studies indicates that disintegration exists in the comprehensive understanding of AI's impact on SCM (Cannas et al., 2023). Investors increasingly allocate resources to AI solutions to enhance supply chain operations. A recent Gartner report states that 50% of CIOs intend to adopt AI (Albanna, 2023).

Prior studies have demonstrated that algorithms provide solutions by fostering innovations to enhance supply chain performance (SCP) (Baryannis et al., 2019 & Nayal et al., 2022). Supply chain literature struggles to stay on track with improvements in AI systems and basic studies (Pournader et al., 2021). The lack of unified information restricts decision-makers, scientists, practitioners, and policymakers (Smyth et al., 2022). AI usage in numerous sectors, including SCM, is remarkable; that's why it is important to map the development, trends, and impact of AI in SCM using the bibliometric analysis method. Bibliometric methods innovatively measure research quality and impact, understand citation processes, map scientific fields, and use quantitative indicators for research policy and management (Helal et al., 2023). The aim of this study is to bridge the gap by analyzing the existing literature using bibliographic techniques. The objectives are to determine prominent authors, core research topics, institutions, and geographical distribution. Finally, it identifies the rising AI and SCM research trends.

The author carries out a bibliometric analysis to examine and evaluate the effect of AI on SCM literature in the period from 2020 to the first quarter of 2024. The objectives are to:

- Identify and analyze publication volume and trends related to the impact of AI on SCM over time.
- Identify and analyze the number of studies published and patterns related to the effect of SCM.
- Evaluate geographical distribution, categorically determining the regions or countries that had the most contributions to the academic research regarding AI-SCM.
- Discovering critical journals and conferences that publish research on the utilization of AI in SCM processes.
- Explore emerging research topics and trends in AI applications within SCM.

- Conduct a citation analysis in order to identify the papers with the most citations, determine influential authors, and pinpoint the impactful institutions operating in the AI-SCM field.

The bibliometric analysis is considered a guide to visualize and get the point of knowledge regarding how AI impacts SCM. This method is highly valued by researchers, planners, and practitioners. Bibliometric analysis as a quantitative method empowers investigators to dive deep into the relevant field and use it as an informational approach. Its outcome is tied to the capacity of well-developed software used for mass data analysis (Helal et al., 2023). Equivalent capabilities grant managers the ability to make informed decision-making, improve technology adaptation, and develop partnerships and innovation in SCM.

This work is the result of a holistic bibliometric analysis that combines interdisciplinary ideas, concentrates on recent developments, conducts network analysis, and delivers practical implications followed with advice for future academic investigations. It offers a thorough and up-to-date perspective on the influence of AI on SCM. The contributions list well-developed academic knowledge and give noteworthy ideas for practitioners utilizing AI-based systems to develop their supply chain processes and performances.

The bibliometric analysis of the impact of AI on SCM encircles research publications on the impact of AI and SCM indexed in the Scopus database from 2020 to the first quarter of 2024. It will capture the evolution of publication trends, the geographical distribution of research contributions, key journals and conferences, emerging topics and trends, and citation analysis of influential papers, writers, and institutions. However, the Scopus database as a single data source excludes related studies listed in other databases. It leads to a partial view of the research. Bibliometric analysis mostly concentrates on quantitative measures. It addresses the qualitative aspects of research innovation and impact partly. Considering the limitations, this analysis targets to deliver a robust and insightful overview of the impact of AI on SCM as reflected in the academic literature.

This thesis is arranged into various topics. The introduction explains why studying AI's impact on SCM is essential and what the thesis aims to achieve. It also

examines what others have already researched about AI in SCM. The Methodology illustrates how data was collected and analyzed from sources like the Scopus database. The final part illustrate the findings of this work, and it outlines the main key findings, limitations, and advice on future research directions.

CHAPTER ONE

LITERATURE REVIEW

The revolutionary invention and a miracle of the century, Artificial Intelligence (AI), has been a transformative force in various sectors, including Supply Chain Management (SCM) (Sharma et al., 2022; Akbari & Do, 2021). AI integration into SCM processes and overall practices is considered an immense change in how organizations manage their supply chains and levels up efficiency, responsiveness, and innovation (Wang, 2022). Processing large datasets, making predictive analyses, and automating decision-making processes are the capabilities that turn AI into an enabling active enabler that allows players in the supply chain sector to adapt promptly, altering and transforming customer demands and unforeseen disruptions, providing a sense of relief about the resilience of their operations. Nevertheless, the possibilities for applying AI in supply chain management have not been fully explored yet (Helo & Hao, 2022)

Global supply chain complexity and the demand for real-time data analysis and decision-making are the factors that fuel the implementation of AI technologies (Belhadi et al., 2022). The effect of the COVID-19 pandemic demonstrated the importance of flexible supply chains around the world. It accelerated AI usage to govern risks and ensure continuity (Trabucco & De Giovanni, 2021).

This chapter, a literature review, examines the impact of AI on SCM, focusing on the developments between 2020 and 2024.

In this study, the author seeks to explore academic publications relevant to AI's application in SCM. Based on the selected timeframe, it covers only articles published between 2020 and 2024. It investigates responses to how AI technologies impact various dimensions of SCM, including logistics and transportation, inventory management, demand forecasting, risk management, decision-making, and operations optimization, which are the critical dimensions most affected by AI. Accordingly, it assesses the impact of AI on supply chain performance and highlights the relevant challenges AI faces during implementation.

The way this literature review is organized about to cover the documented context of AI in SCM, the methodological approaches applied in the latest studies, and their thematic connections. By conducting a bibliometric analysis, this review highlights the most influential works and researchers in AI-SCM. Similarly, it grants a comprehensive list of the current state of research.

The integration of AI in SCM is critical for organizations that are targeting a competitive edge in an increasingly volatile and uncertain market environment. The AI technologies, such as machine learning (ML), deep learning, and natural language processing (NLP), enable supply chains to be more responsive and adaptive (Akbari & Do, 2021; Sharma et al., 2023). These innovative technologies support different programs and systems. Predictive analytics in demand forecasting, autonomous vehicles in logistics, and smart inventory management systems are associated with the mentioned technologies (Min H., 2019; Kumari et al., 2023; Walter, 2023).

Supply chain managers can make better decisions using real-time mass data analysis and guarantee the lowest cost and high efficiency. For instance, AI's predictive analytics technique improves the accuracy of demand forecasting. This leads to ideal inventory levels and minimum waste (Belhadi et al., 2022). AI-based automation systems used in logistics minimize the usage of manual processes and human involvement at all levels of SCM. They improve supply chain operations and counters, and find solutions for the risk of human errors.

As per Brynjolfsson and McAfee (2017), AI was first introduced by Prof. John McCarthy and his team in 1955. AI was introduced, enabling machines to copy human intelligence. It determines, analyzes, and performs tasks comparable to humans. This capability is used through Machine Learning (ML) and Deep Learning (DL) algorithms (Sharma et al., 2022). AI is a segment of the computer science field. It improves systems that can perform tasks that generally demand human intelligence (Kumar, 2021; Pournader et al., 2021). AI technologies, like deep learning, machine learning, and generative adversarial networks, offer significant benefits in SCM. Efficient analytics and improved decision-making are the primary benefits of AI (Mitra et al., 2024). Predictive analytics, task automation, enhanced supply chain

visibility, and personalized customer experiences are the known outcomes of AI usage in SCM (Min H., 2019; Kumari et al., 2023; Walter, 2023).

Generally, the supply chain is a thorough system containing the complete production and distribution processes. It can start from suppliers to the end customer. Its primary goal is to fulfill customer demand, improve responsiveness, and set a network among different stakeholders (Helo & Hao, 2022). Supply Chain Management (SCM) covers the movement of goods and services amid the origin point and the final users (Zott et al., 2013; Dlamini, 2017; Meng, 2021). It is affecting various processes such as transportation, storage, and inventory management (Noman et al., 2022). Within the green supply chain framework, environmental protection and social considerations are also included (Guan et al., 2022). In the circular supply chain context, a consolidated zero-waste approach is added (Tseng et al., 2022). SCM has the capacity to establish smooth operations. It affirms business effectiveness and responsiveness (Bassiouni et al., 2024).

Several academic studies and individual implementations have proven that AI and ML enhance SCM by improving decision-making in different aspects, and these decisions can be autonomous (Mallesham, 2022). The study also shows that AI algorithms have improved data processing significantly, much faster than humans, and this facilitates rapid and efficient decision-making (Kumari et al., 2023). ML, Natural processing (NPL), DL, robotics, and computer vision are AI tools implemented into SCM processes to increase efficiency and effectiveness (Yang et al., 2023; Joel et al., 2024).

The conceptual framework targets combining new technologies with traditional supply chain functions; for example, functions are procurement, production, logistics, and inventory management. Informed decision-making and its values are outlined. This element is critical when AI-based algorithms arrange a high volume of data and positively affect supply chain performance (Taseen & Ali, 2023).

Several AI technologies, such as Machine Learning (ML), Deep Learning (DL), Natural Language Processing (NLP), Computer Vision, Optimization Algorithms, Simulation and Modeling, Generative AI, Predictive Analytics, Robotics Process Automation (RPA), Blockchain, and the IoT, Integrations are applied in SCM.

However, the last four technologies are basically not AI technologies, but they either they are overlap with AI technologies or complement each other.

Machine Learning (ML), generative AI, and deep learning (DL) are among the most transformative AI technologies currently being applied in SCM. These technologies create and improve capabilities for analyzing mass data, which facilitates the recognition of patterns, improves processes, and forecasts forthcoming outputs (Ababou, 2024; Hosseinnia Shavaki, F., & Ebrahimi Ghahnavieh, A., 2023).

As Iliasse et al. (2020) stated, ML algorithms are central to integrating AI in SCM, utilizing supervised, unsupervised, and reinforcement learning techniques. ML is a subset of AI that concentrates on systems that learn from data and improve over time without explicit programming. ML is about improving the outputs through learning and understanding from existing data (Zhao, 2024). AI methods let practitioners and managers improve inventory management and achieve efficiency in demand forecasting (Kumar et al., 2024).

Similarly, by launching predictive maintenance, they can avoid interruptions and mismanagement (Pournader et al., 2021; Stranieri et al., 2024). Ababou (2024) highlighted that Akbari & Do (2021) believe that, over time, the ongoing learning, adaptability, and efficiency can be improved in SCM systems. Firms can optimize their inventory levels, reducing costs associated with inventory surplus or inventory depletion via ML-supported techniques (Cadavid et al., 2018). Zhao (2024) explains and confirms the impact of ML on SCM. He conveys that academic interest has grown. Inventory management, logistics, demand forecasting, quality management, and risk mitigation have been exclusively making the center topics, which have attracted the scholars the most (Ababou, 2024; Hosseinnia Shavaki, F., & Ebrahimi Ghahnavieh, A., 2023).

Guo et al. (2016) define deep learning (DL) as the number one technological approach to measuring upcoming growth. Shrestha and Mahmood (2019) say that DL is a novel learning algorithm. It utilizes a multi-layer neural network, a subset of machine learning, to uncover different levels of a distributed model. It impacts multiple areas, including cancer treatment, personalized medicine, fully autonomous cars, predictive forecasting, and speech recognition (Hosseinnia Shavaki, F., &

Ebrahimi Ghahnavieh, A., 2023; Hu et al., 2021). Numerous DL algorithms have been created by both practitioners (such as software companies and departments) and researchers, including Deep Neural Networks (DNN), Recurrent Neural Networks (RNN), and Convolutional Neural Networks (CNN) and their various adaptations (Hosseinnia Shavaki, F., & Ebrahimi Ghahnavieh, A., 2023).

According to Deng & Yu (2014), Artificial neural networks (ANNs) are designed to replicate brain cell functions, and they fall under deep learning (Hosseinnia Shavaki, F., & Ebrahimi Ghahnavieh, A., 2023). These networks learn from experience using interconnected memory to recognize patterns and process complex data through weights, inputs, and biases. Different types of deep neural networks, like convolutional neural networks (CNN) for computer vision and recurrent neural networks (RNN) for speech error back-propagation, have proven effective in hierarchical planning, optimizing lot sizes, linking inventory with scheduling, and demand forecasting (Sharma et al., 2022).

The organizations that are active in the SCM field can benefit from the strength of both ML and its sub-branch DL technologies in terms of greater understanding, sharper forecasting, and operational effectiveness.

The huge number of articles available on different platforms and newsletters informs us that AI applications in the SCM field are growing proportionally. AI algorithms were used widely in data entry and order processing in the primary stage of AI adoption in SCM. The integration of AI into other parts of business came with the further advancement of AI technologies. It concluded additional complex functions and tasks. For example, AI was used in demand prediction, predictive analysis, and its popularity; its integration in SCM has hit other parts of the businesses, and it has begun to include more complicated functions and tasks like demand forecasting, predictive analysis, and automated logistics (Kumari et al., 2023).

In order to achieve a notable advantage, SCM seeks to digitalize business processes, integrate stakeholders and assets, and align products with customer needs (Helo & Hao, 2022). Digitalization of supply chain processes contributed to the mass data collection. This was important for smoothing the groundwork for AI use in the field of SCM (Hennelly et al., 2020; Kumari et al., 2024).

In the year 1950, linear programming algorithms scored the initial usage of AI in SCM. It helped to develop logistics and inventory management. The next advancement of AI usage in SCM occurred in the years between the 1980s and the 1990s. At this stage, Inventory Management Assistants (IMA) employed AI-driven techniques to duplicate human intelligence. Its output enhances supply chain approaches. In the 2000s, the empowerment of computing, followed by cost-efficient hardware, facilitated the evolution of AI and Machine Learning (ML), leading to capabilities such as inventory management, predictive analysis, and optimized risk management. The revelation of the Industrial Internet of Things (IIoT) and big data in the 2010s made AI further attractive. Montanino (2023) argues that IoT systems compile data in real time, and such outcomes grant AI an incredible capability. This capability guides AI in enhancing supply chain performance and efficiency.

The COVID-19 pandemic in 2020 impacted various industries, including SCM. It was noticed that the prolonged physical flows and reliance on multi-tier suppliers across different regions turn the global supply chains significantly fragile (Giovanni, 2020). The complexity of global disturbances enables firms to understand and predict short-term risks via traditional systems (Trabucco & De Giovanni, 2021). Therefore, stakeholder demand for agility, resilience, and flexibility grew. This way, the need for AI-based solutions increased (Sharma et al., 2022). According to Giovanni (2020), to overcome the challenges, firms accelerated the adoption of AI-technology solutions within their processes (Trabucco & De Giovanni, 2021).

AI in SCM has transformed from basic expert systems to advanced ML systems and autonomous supply chains in recent years. As AI advances, its impact will continue to grow. It presents businesses with greater efficiency, cost reduction, and competitiveness (Montanino, 2023).

Although the variables that connect AI with SCM are complex, they still uphold various benefits (Norgren & Hägglund, 2023). AI technologies have been applied across various areas of SCM, each offering unique benefits and challenges. AI applications in SCM include supply chain network design, supplier selection, inventory planning, demand planning, and green supply chain management (Sharma

et al., 2021). Following is the list of a number of key fields that AI has impacted the most:

1.1. AI in Inventory Management and Demand Forecasting

Inventory Management and Demand Forecasting: Inventory Management marks the main center of a successful SCM. Operational usefulness and buyer satisfaction bolds out the inventory management as a pivotal segment of business (Bhoite, 2024). While meeting customer demands is a top priority, organizing and keeping the optimal stock levels without incurring oversized inventory costs is crucial. It is possible to optimize inventory levels by using a number of AI techniques. Predicting demand patterns and altering stockpiles are the known examples (Kaur et al., 2023). AI assists businesses and firms in decreasing holding costs. And improve supply chain efficiency (Kumar et al., 2024).

In addition to predicting demand and optimizing inventory levels, AI automates replenishment processes by analyzing historical data (Sodiya et al., 2024). AI algorithms can analyze sales data and reorder automatically when stock levels go below a certain threshold. While the algorithms reduce manual intervention and ensure inventory is replenished promptly, they prevent stockouts and improve overall supply chain efficiency (Kaur et al., 2023; Stranieri et al., 2024).

AI and ML technologies utilized in stock management improve productivity. It lessens expenses. Better demand forecasting leads to ideal inventory management. Better demand prediction is easing restocking processes. Lower stockouts followed by maximized inventory turnover boost profitability (Mehla & Raman, 2023). Actors can now forecast demand trends, optimize inventory levels, and identify possible supply chain problems in real-time through the application of AI and ML (Ababou, 2024; Banur et al., 2024). Current information about errors leads to better decision-making.

1.2. Logistics and Transportation

Arunmozhi et al. (2022) highlight how AI-powered robots, drones, and automated vehicles are revolutionizing logistics. These technologies enhance speed and efficiency through automated operations, rapid and affordable delivery, and continuous, cost-effective transportation. AI further optimizes safety, route planning,

delivery speed, and overall operational security and cost-effectiveness, propelling logistics to unprecedented levels. They help lower costs, reduce energy usage, and decrease computation time while simultaneously improving performance and increasing customer satisfaction (Bhargava et al., 2022). Optimizing route selection via AI technologies allows for the selection of the shortest possible route, studying patterns and errors, assists in informed decision making, risk mitigation, and efficiency and factoring in weather conditions helps with preventing risks, selecting the best available means for delivery and finally main goals such as fastest delivery times and lower shipping cost is achieved (Kumari et al., 2023). Robots that have been built based on AI technologies have improved logistics performance and have been proven to be beneficial. They offer fast speed and unparalleled comfort in numerous fields. Warehousing, logistics, and transportation can be affected by these technologies (Wang, 2022). In transportation and distribution, models like the Vehicle Routing Problem (VRP) and shortest path algorithms effectively improve operational efficiency, guaranteeing products are delivered on time and with high quality (Zhang, H. et al., 2022). AI is being used in drone technology to facilitate last-mile delivery, particularly in areas that are difficult to reach by traditional means (Li, J. 2024). According to Iranmanesh et al. (2019), using drone technology has accelerated the speed of fast package deliveries (Bhargava et al., 2022). Automatic inspection methods provide timely internal deliveries and minimize damage within logistics nodes (Zhao, 2024).

1.3. Procurement and Supplier Management

According to Suvittawat (2017), the primary goal of procurement is cost management. It includes cost-effectiveness and quality at the same time. Other priorities are optimizing total procurement costs, improving internal processes, securing supplies, ensuring cost transparency, meeting quality standards, minimizing warehouse expenses, reducing the number of suppliers by focusing on strategic ones, collaborating on product development with suppliers, and outsourcing both operatives and strategic procurement processes where feasible (Chopra, 2019). AI has changed procurement processes and performance. AI systems employing machine learning predict supplier behavior, enabling businesses to mitigate disruptions. Gartner's 2022

report indicates that AI-powered supplier performance management can boost operational efficiency by up to 25% by automating performance reviews (Celestin et al., 2024).

A study by Knapp et al. (2024) revealed that 67% of chief procurement officers prioritize AI in their planning for the next ten years. A fully autonomous request-for-quotation process can lead to higher price quotes from suppliers, as they tend to price-discriminate against less sophisticated AI buyers. AI-based automated systems change wholesale prices widely (Cui et al., 2020).

Generative AI has taken chatbot technology, which "makes data read and speak," a step further. Generative AI is about "making data create," meaning producing human-like creative output, such as new content and solutions similar to strategic approaches and contracts. Generative AI has changed traditional procurement approaches to new heights. Generative AI enhances procurement aspects such as efficiency, productivity, risk mitigation, spending reduction, innovation, sustainability, and compliance. There is a need to replace the traditional roles and functions and adapt them with an AI-based environment. In order to accelerate the integration of AI into procurement, businesses must recognize target use cases, create an AI strategy and environment, redesign the operating model, rebuild the workforce, and accelerate and expand relationship management (Knapp et al., 2024).

AI-supported systems can analyze supplier performance and identify the best sources of raw materials. Having such ability, the businesses can improve their procurement processes and minimize the risk of supply chain setbacks.

1.4. Supply Chain Operations

There is a need to understand how AI fosters capability building at the supply chain level despite its isolated application in various areas (Pournader et al., 2021). AI can improve supply chain operations by enhancing efficiency, enabling real-time decision-making, providing predictive analytics for market trends and risk mitigation, automating day-to-day tasks, enhancing agility to adapt to market changes, improving supply chain visibility, and offering personalized customer experiences (Singh, 2023; Jogarao et al., 2024). Helo and Hao (2022), in behavioral operations, AI-enabled real-

time information sharing enhances supply chain relationships, integration, and coordination among stakeholders (Sharma et al., 2022). These capabilities ultimately lead to the optimization of SCM performance (Wang, 2022). As Wamba et al. (2021) and Dubey et al. (2020) emphasized, AI helps organizations identify shortcomings within SCM and assign resources (Cannas, 2023).

A study by Banur et al. (2024) examined and compared the data from 2016 and 2020. It concluded that the use of robots and automation in the operations chain has accelerated almost equally to their use in executives' production networks.

1.5. Efficiency Advances and Cost Reductions

One of the most significant impacts of AI in SCM is improving operational efficiency and reducing costs (Singh & Adhikari, 2023). AI technologies automate various processes within the supply chain, the need for manual labor goes down, human error is minimized, and cost efficiency is achieved (Wilson et al., 2024). Consequently, more rapid processing, lead time decrease, cost lowering, and improved prevailing efficiency are obtained (Cannas, 2023).

AI technologies, including ML integration to SCM, have greatly affected retailers' operations, process optimization, and customer experience (Mehla & Raman, 2023). According to Kumar et al. (2021), the revolution of e-commerce, shift in customer tastes, and intensified competition factors have changed the retail industry significantly. AI and ML capabilities enable businesses in the retail domain to survive and succeed. Customer satisfaction is a crucial success factor. These technologies, or "smart retail practices," assist businesses in improving efficiency, enhancing services, and offering unmatched products and services, followed by higher productivity and lower costs. These technologies develop smart retail environments through operational efficiency, reducing risk, and offering prospects to boost customer-centric initiatives (Mehla & Raman, 2023).

Robotics and automation enhance SCM. They reduce enduring expenses and amplify work and usage strength. Also, they minimize errors, decrease repetitive stock checks, manage times, and assemble induction to problematic and hazardous places. Robotics aids in design, creation, etc. Automated robots equipped with cameras can

realize objects and materials and speed up picking. AI can elevate customer satisfaction, improve evaluation of flows and resources, enhance quality and customer experience, update data gradually, speed up the picking process, reduce stockpile risk, assist with risk mitigation, reduce waste, and minimize errors. A brief example of picking is that each stored object is mechanically taken out from a warehouse and delivered to a picker or pick location (Banur et al., 2024).

In Logistics, AI-powered route optimization reduces fuel consumption and transportation costs by determining the most efficient routes for delivery. Similarly, AI-powered predictive maintenance reduces equipment downtime and maintenance costs by predicting when machinery will likely fail and scheduling maintenance before issues arise (Arunmozhi et al., 2022; Bhargava et al., 2022). The technologies and techniques illustrated above all reduce costs and enhance efficiency in every step of SCM operations and processes.

1.6. Enhanced Decision-Making Capabilities

AI-based technologies have been widely used in many industries and are extremely popular now. Still, it has not been fully used in decision-making processes within the SCM domain (Sadeghi et al., 2024). Recent literature indicates a gradual shift in this trend (Sharma et al., 2022). As Sellitto indicates, organizations use AI tools extensively in various supply chain operations to enhance decision-making, particularly in inventory management, demand forecasting, risk management, and sustainable SCM (Rana & Daultani, 2023). AI enhances decision-making capabilities within the supply chain by providing real-time insights and predictive analytics. These technologies improve decision-making capabilities, decrease cycle times, and enhance operational efficiency within the processes of SCM (Sharma et al., 2022). Managers may use AI-based technologies such as explainable artificial intelligence to obtain fundamentally important information associated with the decision-making processes. This capability lets them know the logic behind AI results and identify possible exposures (Sadeghi et al., 2024). These techniques and prospects motivate supply chain managers to make informed decisions and improve the responsiveness and resilience of the supply chain processes (Baryannis et al., 2019; Jogarao et al., 2024).

Analytics platforms empowered by AI-based algorithms manage to monitor the performance of supply chain processes in real time. It feeds up-to-date information to administrators and managers on key metrics consisting of transportation costs, delivery time, and inventory level. These capabilities lead to the on-time identification of errors within the processes and facilitate immediate troubleshooting of problems prior to them spreading (Kumari et al., 2024; Sadeghi et al., 2024).

AI Predictive analytics powered by AI also enables supply chain managers to foresee forthcoming directions and push proactive decisions (Belhadi et al., 2022). AI presents support anytime logistics and supply chains are disrupted by natural disasters or other threats, allows for exceptional inventory and warehouse efficiency, decreases human errors with automation, creates safer and sound work environments, enables on-time decision-making, and furnishes the possibility of predicting demand. Issues such as the complexity and costs of AI technologies are the concerns raised by individual businesses, and the experts advise that these issues can be solved by navigating the bottlenecks by selecting the right vendor and perfect planning (Ismaeil, 2024).

1.7. Risk Management

Managing a resilient supply chain has become increasingly important in today's turbulent and unpredictable market environment. AI-based systems facilitate the tools to recognize and mitigate risks before they impact the supply chain (Mohsen, 2023).

AI techniques can be used to determine risks in the supply chain, like supplier failures or transportation delays, and develop strategies to mitigate these risks. AI-based risk management systems are doing massive data analysis to identify risks. Transportation delays, supplier failure, and natural disasters are the potential risks that can be recognized by such systems (Usmani et al., 2023).

They evaluate the potential impact of these threats. Then, it suggests mitigation strategies. Diversifying suppliers or rerouting shipments are known examples. These approaches enable practitioners to achieve a more useful, flexible supply chain that avoids disruptions and functions seamlessly (Baryannis et al., 2019; Gupta et al., 2022). AI creates additional conditions and evaluates the supply chain's resilience.

AI-based tools that demonstrate the consequences of multiple disruptions on the supply chains, and this can be taken as a typical example. Supplier breakdown and transportation delays are other familiar disorders that AI tools can identify. This allows companies to test their contingency plans and identify potential weaknesses in their supply chain. This action deters the potential actual risk (Ivanov & Dolgui, 2021; Naletina, 2021; Usmani et al., 2023).

By analyzing the outcomes of past efforts in AI-SCM implementation, practitioners can draw insights from previous AI-SCM applications and create their own best practices (Sharma et al., 2022).

1.8. Challenges and Barriers to AI Adoption in SCM

AI offers numerous benefits to SCM. Still, its adoption is difficult. Many studies have found that the technological constraint of AI systems is the number one barrier in SCM (Singh & Adhikari, 2023). These limitations include the high cost of AI technologies. Second, the complexity of implementing AI systems, and third, the lack of technical expertise in many institutions (Pournader et al., 2021).

To implement AI in SC, huge investment is required. The major areas that require more investment are hardware, software, and infrastructure. Additionally, organizations need access to large datasets to train AI models. Accessing large datasets is challenging in some industries. AI implementation requires specialized technical skills, which many organizations lack. From this outcome, we can understand that these barriers have slowed down the process of applying AI-supported technologies in a number of businesses. For example, small and medium-sized enterprises (SMEs) have been the primary victims of such a problem (Cadavid et al., 2018).

Hangl et al. (2023) have underlined that data challenges also established a substantial roadblock to AI utilization in SCM. AI technologies depend on large amounts of data to work effectively, but many organizations struggle to collect, store, and analyze this data. Data quality is another concern, as inaccurate or incomplete data may cause wrong predictions and decisions (Shrivastav, 2021). Data privacy, security, and existing regulations and standard procedures are important challenges, especially in sensitive information industries (Hangl et al., 2023).

While other problems exist, organizations face resistance internally as well. Managerial and intra-organization factors are the main reasons (Bag et al., 2023). The first reason for the resistance is the lack of information regarding AI systems. The second and the most common reason is the fear of job loss among employees (Hangl et al., 2023).

Organizational culture contributes significantly to the implementation of AI systems. The firms that struggle with internal resistance to change are not choosing AI and other new technologies. (Shahzadi et al., 2024). Resistance may show up in different forms. Unwillingness to invest in AI, doubt about the possible advantages of AI, and fear of disrupting the existing processes are the known forms of resistance (Conboy et al., 2020; Shahzadi et al., 2024).

Job displacement and employees in roles susceptible to automation are the fears that many organizations have experienced. These anxieties are considered a job security threat. That is why they have fueled resistance to adopting AI technologies. Effective communication, change management strategies, and commitment to training and improving employees' skills, businesses can remove the mentioned concerns. The easy way is to convey a simple message, "working with AI side by side" (Bag et al., 2024).

The adoption of AI in SCM extends essential ethical and regulatory concerns as well (Singh & Adhikari, 2023). The rapid growth of AI technologies raises the need to address data privacy, ethical use of AI, and AI bias day by day (Adali, 2023). AI-driven SCM often involves collecting, processing, and sharing massive data. This may include sensitive customer and supplier information. Biases could be supported by AI algorithms during data training and may lead to improper decisions at different stages. Removing bias and ensuring fairness in AI models is essential (Singh & Adhikari, 2023). General Data Protection Regulation (GDPR) of Europe and similar institutions impose tough requirements on how data is collected, stored, and used (Georgiopoulou et al., 2020).

Algorithmic bias in AI-supported systems remains a point of concern for developers and professionals. Thiem et al. (2020) and Tsamados et al. (2021) point out that poor training data causes AI-based systems to make unfair or discriminatory

decisions (Akter et al., 2021; Islam et al., 2024). Due to algorithmic bias, the chance of accidentally benefiting a specific supplier during the selection stage remains high. Similar issues are not perceived as a proper business act (Dubey et al., 2022). Careful attention to data allocated for use in AI systems, constant monitoring, and adjustment of algorithms accordingly assists in ensuring fairness and clarity (Cadden et al., 2022). Regulatory matters are also in the row of challenges for AI use in the SCM field (Ganesh & Kalpana, 2022). AI technologies and techniques grow exponentially. Governments and regulatory institutions are trying to establish perfect and meaningful legal frameworks for AI integration in various areas. These efforts cover many industries. But their efforts don't fully fulfill the current need. The issue creates ambiguity for organizations operating in different industries (Tumpa et al., 2019). Many businesses take roles and regulations seriously, and any vagueness can stop them from investing in AI applications used in the industry in which they operate. Using advanced cybersecurity and following data protection regulations helps prevent breaches; awareness and compliance with related regulations are essential, and legal consultations followed by compliance audits assist with ensuring complex regulatory policies (Singh & Adhikari, 2023). Companies that maintain an ethical AI supply chain can positively influence the industry (Muldoon et al., 2023).

1.9. Future Directions for AI in SCM

The future of AI in SCM will likely be shaped by several emerging trends and technologies currently in the early stages of development. These patterns include the integration of AI with the IoT, the use of blockchain technology for supply chain transparency, and the adoption of AI-driven digital twin systems for supply chain simulation and optimization (Xiang et al., 2024; Arunmozhi et al., 2022; Moshood et al., 2021).

Different studies confirm that the merging of AI and IoT improves SCM. It fosters live data gathering and analysis from linked devices through the supply chains. IoT devices and systems, like sensors and Radio Frequency Identification Devices (RFID) tags, are able to provide valuable data on inventory levels, transportation conditions, and equipment performance. By analyzing these data, AI improves supply

chain operations, improves decision-making, and enhances predictive maintenance (Unhelkar et al., 2022; Chanchaichujit et al., 2020; Ikevuje et al., 2024).

Blockchain systems are famous for their capability to deliver protection and transparent records. A great interest exists in blockchain use in SCM. A combination of blockchain and AI provides healthy and transparent supply chain transactions. It can cover transactions from procurement to shipments to the end users. (Arunmozhi et al., 2022). AI algorithms are the best solutions for analyzing blockchain data and visualizing trends and uncertainties. Compliance with rules, fewer drawbacks, and scam deterrence are the least likely outcomes of such analysis.

Digital twins (DT) are considered a virtual presentation of physical supply chains. They are another emerging technology with substantial potential in SCM (Nguyen, 2022). During the rise of the COVID-19 pandemic, researchers began to recognize the potential of DT in enhancing supply chain resilience to address disruption risks (Ivanov & Dolgui, 2021). Digital-twin systems have the capacity to evaluate all available options and measure the efficiency and performance of SC processes. AI systems study these practices and equip managers to make decisions based on data, boost effectiveness and flexibility, and strengthen the processes of supply chains (Moshood et al., 2021).

1.10. Bibliometric Analysis in SCM Research

According to Small (1999), the bibliometric analysis method is a science mapping technique (Mageto, 2022) that visually represents the relationships between disciplines, fields, areas of expertise, and documents or authors (Rana & Daultani, 2023). Bibliometric research focuses on quantitative analysis of literature (Koseoglu et al., 2023). AI-supported methods systematically examine publication patterns, citation analysis, and keyword trends, providing a cohesive overview of the field (Chen, 2006). As per Ding et al. (2001), bibliometric analysis helps scientific fields and uses quantitative indicators for research policy and management. One of the jobs that researchers who launch bibliometric (Bibliometricians) analysis have been recording all advancements in the bibliometric analysis domain and offering prospects for its transforming attributes (Mejia et al., 2021). According to Feng et al. (2017), bibliometric analysis has various benefits compared to classic methods. Content

analysis is the capability to refine a large number of publications and analyze their citations, correlations, and keyword analysis. The bibliometric method offers such a major advantage (Sharma et al., 2022; Mejia et al., 2021). Considering the SCM context, the bibliometric practices enhance the definition of improvements in AI-linked publications and significant scientific works. It enhances the level of cooperation among scholars and the scholarly community (Sharma et al., 2023).

Citation analysis, h-index, and impact elements have a long history, but they are still used. Webometrics, open access, and visualization are considered newer areas. Moreover, they are gaining excellence in bibliometrics studies (Mejia et al., 2021). The process of bibliometric analysis generally involves several phases. It starts with data collection from online platforms. The known databases used by this method are Scopus and Web of Science. The retrieved dataset is analyzed to pinpoint trends in publication activity, citation patterns, and the distribution of research subjects (Mejia et al., 2021; Sharma et al., 2023). The analysis generates results that are used to identify the most influential researchers, publications, and institutions operating in the SCM field. Also, it highlights the research gaps and emerging trends.

Intellectuals create valuable outputs with the help of bibliometric analysis to evaluate the impact of AI in SCM research and academic works. Bibliometric analysis reveals how AI has impacted the SCM domain. This method underlines the most major research themes. It identifies leading researchers and institutions, and shows the geographical distribution of AI SCM studies (Zejjari & Benhayoun, 2024; Donthu et al, 2021). These trends and patterns empower the investigators to understand the ongoing state of AI utilization in the SCM environment. They can acknowledge and raise potential areas for additional exploration (Zejjari & Benhayoun, 2024).

The periodic bibliometric analysis of AI-SCM demonstrates and compares the level of attention that two specific topics, demand prediction study and logistics optimization, have obtained. Equivalent information recommends forthcoming research initiatives. The information assists the underexplored areas to get the deserved attention (Rana & Daultani, 2023).

Bibliometric analysis displays collaboration networks among AI-SCM researchers and institutions. Their cooperation fosters new partnerships and extends to various fields (Koseoglu et al., 2023).

Using AI in SCM has gained considerable advancement and popularity. Still, several research opportunities and gaps exist. Understanding the potential opportunities and gaps urges scholars and investigators to take more steps and continue additional investigations. Further investigations are necessary to recognize and understand AI's impact on the SCM field. he need for AI synchronization with blockchain and IoT technologies exists. This area can be highly important for scientists and practitioners to evolve further. These technologies hold great promise. Still, additional investigation is required to know how they can be integrated into supply chains effectively. It is also important to learn their potential benefits and challenges they face (Chanchaichujit et al., 2020; Arunmozhi et al., 2022; Unhelkar et al., 2022; Montanino, 2023; Xiang et al., 2024). The ethical and regulatory impact of AI on SCM procedures is vitally important to explore. This can be a topic for future research. Key ethical reflections are data privacy, algorithmic bias, and the effect on performance. Instructing the safe and reliable usage of AI in the SCM field requires numerous academic studies and developing regulatory frameworks (Taeihagh et al., 2021; Hangl et al., 2023).

AI's utilization in factory automation, vehicle automation, and other machinery or processes is creating concerns among workers about job security. This issue leads to corporate resistance (Sharma et al., 2022). Analyzing the human aspects relevant to AI applications in SCM can overcome the above-mentioned concerns. Such studies will address understanding the AI integration into existing organizational systems, gaining the required skills by employees to work alongside AI-supported systems, and finally, overcoming the resistance to AI adoption. Studies in this area can help businesses resolve the problems linked to the implementation of AI (Shrivastav, 2021; Sharma et al., 2022).

Combining ML techniques with mathematical programming models facilitates to achieve a more effective supply chain. Future research facilitates to combine such

combinations to examine new operational structures. A Theoretical model can be created to study the relationships amid different industries (Zhao, 2024).

More holistic research is needed to combine fragmented information. This is essential for visualizing a better image of AI's use and its impact on the SCM domain. Previous data security and privacy roles and regulations are huge challenges in front of AI implications in SCM. Detailed research can help to understand the complexity of existing challenges and deliver exclusive solutions. It is a common understanding that AI enhances resilience in supply chains.

The implementation of AI in the SCM domain has been considered an exclusive advancement during the last few years (Akbari & Do, 2021 & Nguyen, 2022). AI-based technologies, like ML, DL, and predictive analytics, have converted various aspects of SCM. Demand forecasting, inventory management, logistics, and risk management are the key functions of SCM that have been improved the most. AI-based systems have empowered productivity in the SCM domain, and they have directed effective decision-making and cost savings. It is formed resilience when changes happen in the bazaar circumstances (Khedr & Rani, 2024).

The utilization of AI systems technologies in the SCM field is followed by challenges and obstacles. Technological limitations, data setbacks, organizational resistance, and ethical and regulatory considerations are counted as substantial barriers to AI usage in the SCM domain. Overcoming these problems will require continued investment in AI technologies and research into the best practices for implementing AI in SCM. Pieter Niehues said, "The use of GenAI is inevitable. Those who do not adopt it will fall behind in competition and be replaced - not by GenAI, but by those who embrace it."

This literature review demonstrates AI has the capacity to create opportunities and stages for managers to enhance supply chain performances (Nguyen, 2022). Successful AI implementation needs a strategic approach that considers the unique challenges and barriers associated with AI implementation. The study also showed that investment in all necessary infrastructures and frameworks for AI adaptability is highly recommended. Businesses have to value and consider AI's ethical usage.

This literature review underlines a number of areas for researchers to explore further. These include the integration of AI with emerging technologies, the ethical and regulatory implications of AI, the human factors, and the combination of ML with mathematical optimization associated with AI adoption in SCM. Examining novel topics which has been reviewed within this study and AI's usage in other industries establishes the advancement and maturation of AI-SCM (Sharma et al., 2022).

This literature review reveals that AI progresses and matures, and its impact on the SCM domain will grow further. The next few years will be critical in determining how AI will shape the future of SCM. Using the opportunities presented by AI, organizations can build more effective, flexible, and endurable supply chains capable of meeting the demands of modern markets. Practitioners in the SCM field have to prioritize AI in their future planning. While many people express their concerns over job loss and the ethical ramifications of AI and ML, supporters argue that these technologies can create new job opportunities and that long-term cost savings and improved efficiency make the investment worthwhile (Banur et al., 2024). According to Olan et al. (2022), supply chain organizations will significantly benefit from AI and other emerging technologies (Sharma et al., 2022).

CHAPTER TWO

METHODOLOGY

This study's research design is a quantitative bibliometric analysis. Bibliometric analysis is regarded as a statistical technique that systematically examines books, articles, and other publications (Alrezq, 2021). As Small (1999) explained, the bibliometric analysis method is a science mapping technique that visually constructs the relationships between disciplines, fields, areas of expertise, and documents or authors (Rana & Daultani, 2023; Mageto, 2022). This approach allows for systematically examining publication patterns, citation analysis, and keyword trends within a specific field. According to Feng et al. (2017), bibliometric analysis has various benefits compared to classic methods. Content analysis, which is the ability to refine a huge number of publications and analyze their co-relations, citations, and keyword analysis, is the major advantage offered by the bibliometric method (Sharma et al., 2022; Mejia et al., 2021). The study adds knowledge to the research's development, structure, and impact of AI on SCM from 2020 to Q1 2024.

Geraldi et al. (2011) note that due to its vast collection of peer-reviewed literature, the Scopus database is used for searching and referencing published papers (Sharma et al., 2022). The Scopus and Web of Science (WoS) databases share similarities. Scopus possesses more records than the WoS (Rana & Daultani, 2023).

The front page of Elsevier's website describes the Scopus database as covering 330 fields of study. Such coverage empowers educators, researchers, librarians, and students to have broad access to key information. More access means better research and academic work. It provides unparalleled access to critical research worldwide and holds 10 – 15% more citations than its nearest competitor, leading to more extensive bibliometric and historical trends.

Considering the abovementioned criteria, all relevant publications that aimed to be analyzed throughout this study were collected from the Scopus database. Boolean operators and searching keywords like AND, OR, and NOT were assigned to find related literature efficiently. The Boolean operators (AND, OR, NOT) are valuable

means for scholars who conduct bibliometric studies. Using 'AND' assures precision by retrieving articles holding all specified terms, such as 'AI AND supply chain.

The operator 'OR' expands search results by adding articles with specified terms and counting synonyms or related concepts similar to 'AI OR artificial intelligence. The operator 'NOT' excludes exact terms from search results, refining the search to exclude irrelevant articles, as in 'AI NOT robotics.' The above operators let investigators to make complicated questions, alter search approaches, and guarantee complete coverage of appropriate literature. It was reassuring to see the thoroughness of their research in the Scopus database.

This study covers research publications on the impact of AI on SCM indexed in the Scopus database from 2020 to the first quarter of 2024. An initial search conducted in 2024 retrieved 1773 research papers. The search targeted articles and conference papers only; other papers, such as book chapters, editorials, notes, and unpublished reports, were excluded. According to Lamba & Singh (2017) and Ramos-Rodríguez & Ruíz-Navarro (2004), such papers present basic search or unreliable ideas (Sharma et al., 2022). Furthermore, the search was limited by time, subject, keywords, including "Artificial Intelligence, "AI," "Supply Chain Management," "SCM," "Logistics," and "Inventory Management," and language (English), which caused the further exclusion of papers. In order to understand the depth of fragmentation among researchers and find how unified information exists by visualizing trends well, the search was not limited to specified journals. Finally, after applying all the mentioned criteria, 838 articles were selected.

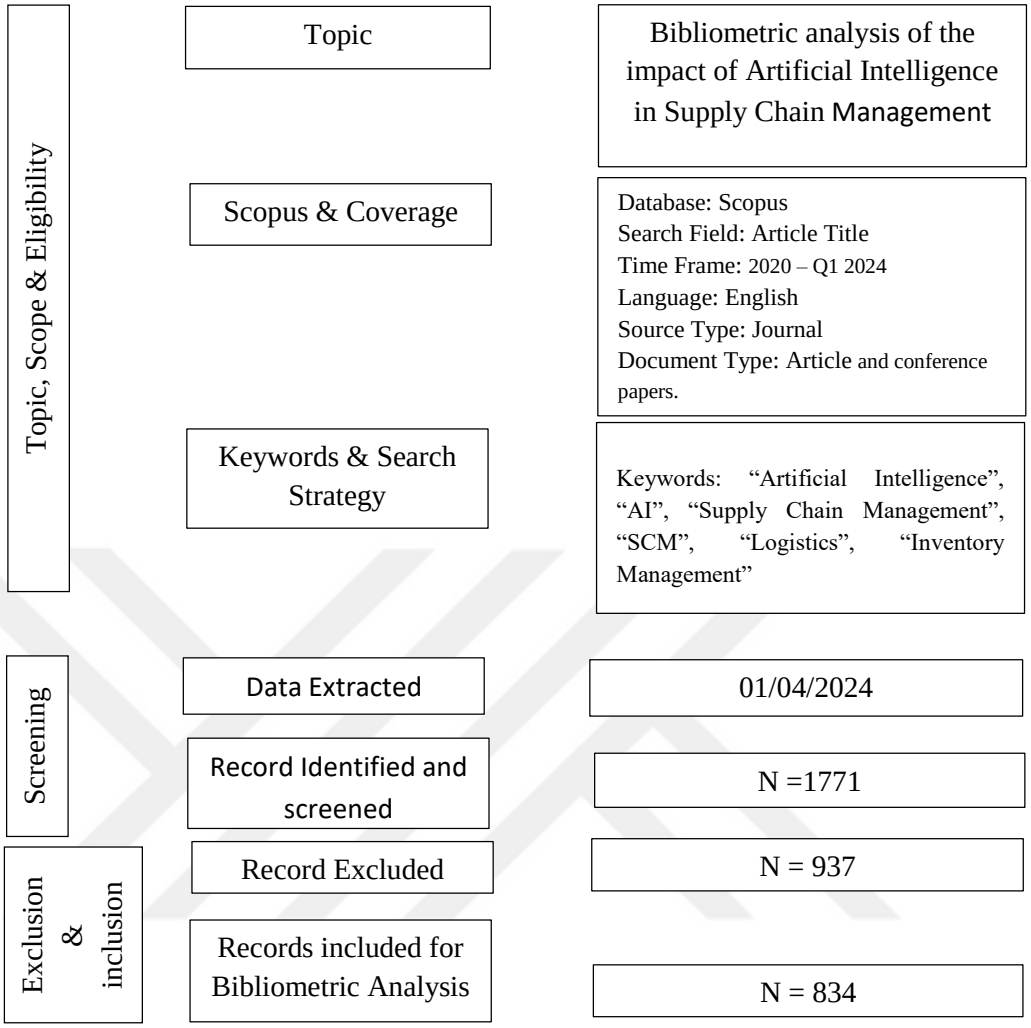


Figure 1. Flow diagram of the search strategy

The visualization feature in the Scopus database displayed exciting information. The feature in the mentioned database makes graphs and charts. It visualizes partner networks, publication trends, and citation distributions. The outcomes enable scholars to learn about the influence and progression of specific research topics over time. Figure 2 presents the number of scholarly documents published each year. The good news is that this graph demonstrates a dramatic increase in published articles from 2020 to 1Q 2024. The vertical line represents the number of publications, and the horizontal line describes the years.

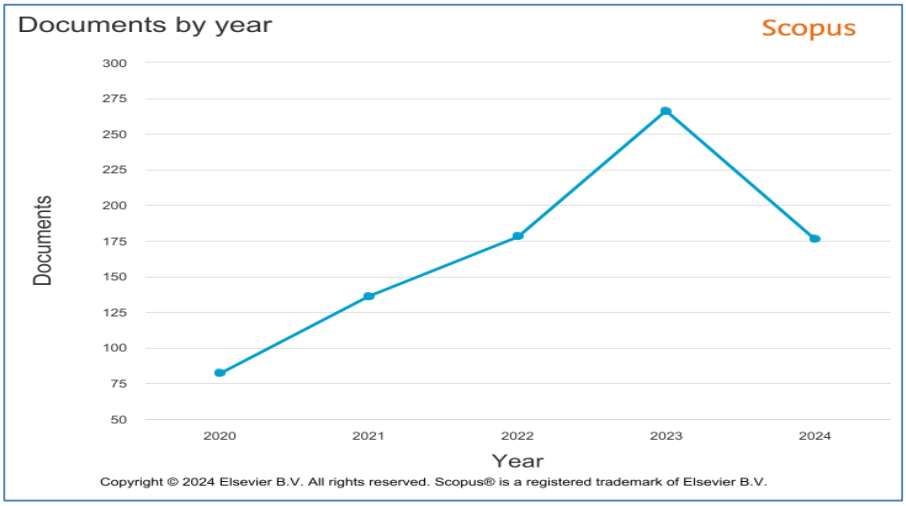


Figure. 2: Document by year

2.1. Bibliometric Analysis Tools

Based on Cobo et al. (2011), Chen (2006, 2014, CiteSpace is a bibliometric analysis software utilized to detect emerging trends, visualize citation networks, analyze co-citation patterns, map knowledge domains, identify research fronts, and conduct keyword analysis. By processing data from comprehensive databases like Web of Science, Scopus, and PubMed, Citespace creates visual representations that reveal relationships between cited and citing papers, influential authors, and critical research topics. CiteSpace software uses different metrics to assess and map the scholarly landscape (Chen, 2020).

Table 1. CiteSpace metrics, as proposed by Chen (2020)

Co-citation analysis	Detects influential articles and authors by evaluating how often two documents are cited together.
Citation burst detection	Notifies studies that have achieved sudden and intensive attention in a specified period.
Betweenness centrality	It is used to identify pivotal nodes in the citation networks.
Cluster analysis	Groups related documents into thematic clusters.
Timeline views	Display the temporal development of these clusters, revealing how research topics evolve.
Term frequency-inverse document frequency (TF-DF)	Identifies significant terms and phrases in the literature.

The node size corresponds to the normalized citation counts in the most recent period. Landmark nodes can be recognized by their large discs. The label size per node is proportionate to the article's citations, so larger nodes also have more prominent labels (Chen, 2004; Chen et al., 2024). In a timeline view, each cluster is organized horizontally, and the time points are on the right (Chen, 2010). The metrics in Table 1 can be further studied in the official Citespace manual and related publications, such as "CiteSpace II: Detecting and visualizing arising trends and brief patterns in scientific publications." Journal of the American Society for Information Science and Technology, 57, (3), 359-377 (Chen, 2006).

2.1.1. Analysis techniques

The analysis of this study employs several quantitative bibliometric techniques to systematically explore and visualize the research landscape of artificial intelligence (AI) in supply chain management (SCM) from the year 2020 to the first quarter of 2024. Data processing involves cleaning and disambiguating author names to ensure consistency (Jogarao et al., 2024). The methods of review used in this study include the following:

2.1.2. Keyword analysis:

This stage helps to find the current status via noticing research directions and emerging topics. It studies the patterns and occurrences of keywords utilized in the publications. The process begins with data collection from bibliographic databases such as Scopus, focusing on relevant metadata like author names and affiliations from 2020 to 2024 (Radhakrishnan et al., 2017).

2.1.3. Authorship and collaboration

According to White & McCain (1998) and Chen et al. (2021), launching author co-citation or co-authorship patterns analysis is used to identify social or academic networks (Newman, 2001; Koseoglu et al., 2021). The authorship and collaboration analysis address the evaluation of the collaborative associations among investigators. This approach analyzes academic publications to achieve its goals. The method helps to illustrate the dynamics and framework of research cooperation. Identifying key

authors, influential groups, and overall connectivity within the research society are the initial outcomes of such studies (Radhakrishnan et al., 2017; Chen et al., 2020).

After data processing, network construction follows, where a co-authorship network is created with nodes representing authors and edges representing co-authored papers (Cobo et al., 2011; Eck & Waltman, 2014); the visualization will be explored by the CiteSpace software. The network analysis includes calculating metrics such as degree centrality and betweenness centrality to understand research collaborations' structure and dynamics (Newman, 2001; Steelman et al., 2021; Morrison et al., 2022). The outcomes are interpreted to identify critical authors and influential cooperative groups, and findings are reported with supporting visualizations to provide a comprehensive view of the research community (Chen et al., 2020).

2.1.4. Citation analysis

According to Daud et al. (2022), citation analysis is regarded as a quantitative method. This method examines the citations of studies, scholarly journals, and researchers to evaluate underlying patterns and quantitative characteristics of their work (Koseoglu et al., 2021, and Koseoglu et al., 2023). Citation analysis illustrates the status of current activities and tells whether the audience has accepted them widely. Citation patterns can indicate the trustworthiness of a publication. Therefore, it offers insights into the credibility of published work(Dhamija & Bag, 2020). Examining the impact and influence of articles, journals, and authors on the AI and SCM field is the main goal of citation analysis.

Citation counts of each research paper are collected. Then it is used to analyze the number of times each article has been cited. This method helps with identifying highly influential works. It directs authors to noteworthy journals. Top N, H index, and impact factor metrics are calculated to evaluate the productivity and impact of study thoroughly.

2.1.5. Co-Citation analysis

Co-citation analysis is an essential aspect of bibliometrics (Koseoglu et al., 2023). According to Benckendorff & Zehrer (2013), co-citation analysis is mainly based on data from the same list of references and having common points. A co-

citation analysis aims to determine the relationships between frequently Co-cited documents, display the intellectual structure, and identify outstanding research clusters within the field.

Co-citation frequencies, a key metric in determining the influence of articles, are analyzed to determine how often pairs of articles are cited together. Network analysis methods are employed to show these co-citation connections, and they showcase clusters of related research. This approach aids in identifying influential articles and learning how different research works are interlinked (Koseoglu et al., 2023).

2.1.6. Thematic mapping

As per Cobo et al. (2011), the thematic analysis is perceived as a persuasive method in bibliometric analysis. It is used to investigate the conceptual structure of a particular research field (Aria et al., 2022). Thematic analysis visualizes research topics' thematic progression and their structure over time. This method presents a creative understanding of the development and expansion of fundamental topics in the industry. New methods and ideas offered by this approach help to understand the structure and advancement of academic ideas in AI and SCM.

Cluster analysis categorizes documents based on thematic similarities, detecting major research themes. Temporal analysis follows the improvement of these topics via different timeframes. Correspondence analysis displays the relationships between documents and their related themes, constructing thematic maps pointing out the progression and structure of scientific ideas in AI and SCM.

This work uses quantitative bibliometric analysis practices to comprehensively and systematically examine the research ground. The analysis assists in the determination of noteworthy studies, emerging patterns, and essential research topics at the interface of AI and SCM. It delivers considerable views for investigators and practitioners in the relevant field.

2.2. FINDINGS

2.2.1. Keyword analysis

The keyword analysis in this study shows the essential themes and their evolution in the context of artificial intelligence (AI) in supply chain management (SCM). The keyword network detected ten significant clusters, with the largest focusing on sustainable supply chain management, intelligent technologies, deep learning approaches, decision support systems, supply chain systems, secure blockchain, using soft computing, supply chain risk management, blockchain applications, and demand forecasting. These clusters reveal the broad and interdisciplinary ways AI is applied in SCM and explain different characteristics like risk management, deep learning approaches, and blockchain applications. The largest cluster, sustainable supply chain management, underscores how AI is increasingly being used to promote sustainability in SCM practices. Cluster analysis demonstrates a dynamic advancement of keywords, with extensive shifts in focus over recent years.

The size of nodes is a visual representation of the frequency or number of occurrences of an item, such as an author or a keyword, in a dataset. The number of members shows the number of items listed in one cluster recognized during the analysis. The silhouette value measures the quality of each item assigned to the specific cluster. Values near 1 show better clustering. The total weight of the links linked to a node is called the strength of a node. It shows its overall connectedness. The degree of centrality determines the number of links a node has with other network nodes. Betweenness centrality demonstrates how often a node falls on the briefest pathway between other pairs of nodes. It highlights the importance of a node in the network flow. A sudden and notable increase in the frequency of impact experienced by an item on a particular period is indicated by a burst.

2.2.1.1. Cluster 0

The sustainable supply chain management with cluster ID number (0) mentioned an average emergence year of 2022, suggesting a recent surge in research willingness. This cluster keeps favorably cited works, like Zhang (2022). It informs the role of big data analytics in improving competitive benefits during the COVID-19 pandemic. The

repeated citation of terms like "supply chain management," "sustainable development", “risk management”, “environmental impact”, and "artificial intelligence marks the cluster's association and influence. Silhouette value of this cluster is 0.947. Figure 3 represents the keyword development through cluster 0.



Figure 3. Keyword evolution across cluster #0.

2.2.1.2. Cluster 1

The "Smart Technologies" cluster shows the emergence of AI with evolved technologies like big data analytics and digital transformation. Zhang (2022) connects green supply chain management activities with competitiveness. The silhouette value for this cluster is 0.941. It explains the unification of AI and sustainable practices. The keywords "big data," "data analytics," and "digital transformation" emphasize the technological forces behind SCM improvements. Table 2 offers a summary of significant clusters, including information on their size, assigned label, and average publication year.

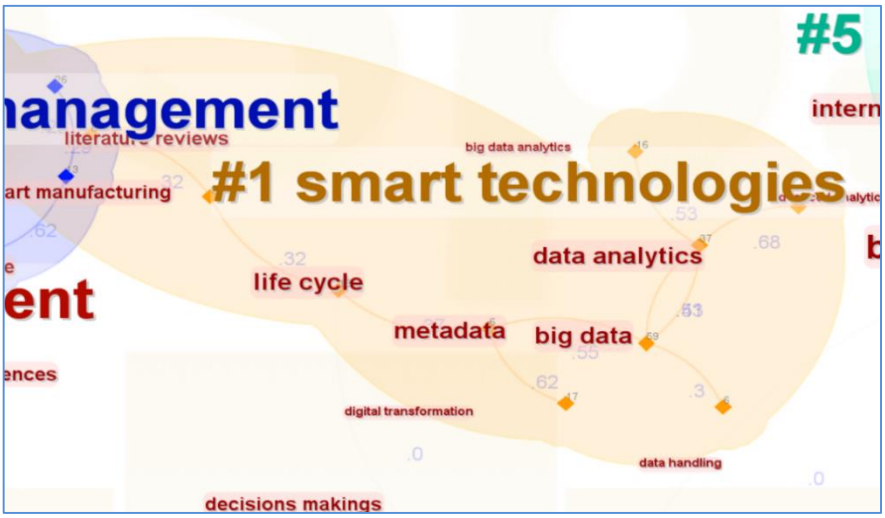


Figure 4. Keyword evolution across cluster #1.

2.2.1.3. Cluster 2

Deep learning approaches have nine members. Its silhouette value is 0.945, showing its profound constancy and thematic unity. Machine learning, with 137 citations, reaches the top of the citation distribution of this cluster, Deep Learning 40, and Learning Systems 32 citations hold the second and third positions. Learning algorithms, Complex Networks, Decision Trees, Predictive Analytics, and Quality Control are the remaining members of this cluster. The high citation count for machine learning shows its role in the cluster and, together with deep learning and learning systems, underlines the increasing adoption of progressive AI models in supply chain applications. Maitra & Kundu (2023) explain the role of AI algorithms in backorder prediction in inventory management.

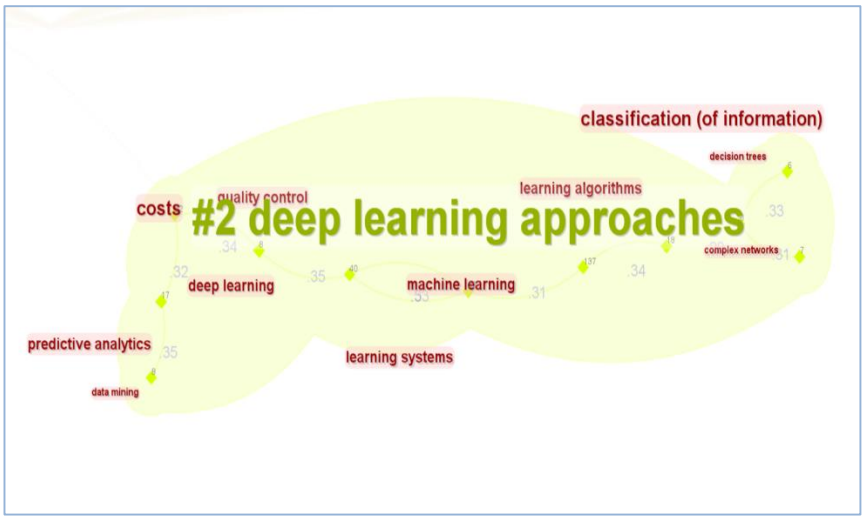


Figure 5. Keyword evolution across cluster #2.

2.2.1.4. Cluster 3

The cluster of decision support systems marks the usage of AI in improving decision-making processes throughout SCM. With an average emergence year of 2022, it stresses AI's effect in organizing supply and demand halt, as Lee (2024) shows. This article was published in 2024 and for the second time in 2025. Its Silhouette value is 1. It suggests decision-making strategies. A cluster analysis revealed that the most frequently cited members within the group were artificial intelligence (682 citations), decision support systems (99 citations), and supply chain (80 citations). The increased citation counts for "artificial intelligence," "decision support systems," and "supply chain" within this cluster list its primary vitality in SCM research.

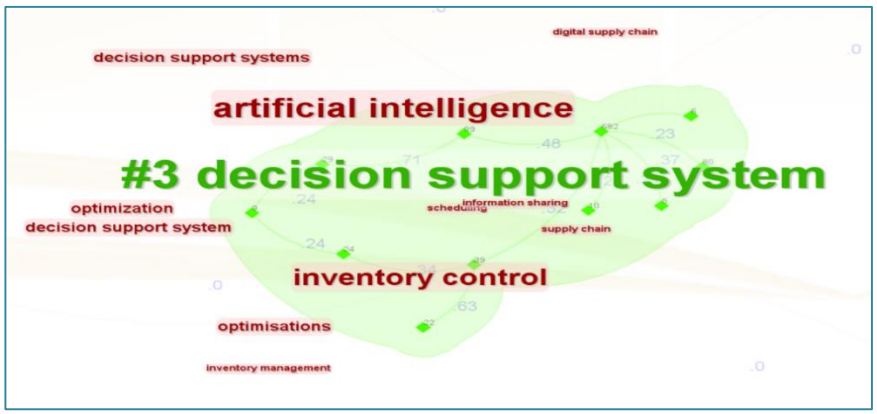


Figure 6. Keyword evolution across cluster #3

2.2.1.5. Cluster 4

This cluster is named "supply chain management" and exhibits a high degree of internal consistency, indicated by a silhouette value of 0.958. This fifth-largest cluster also has nine members. It has been dominated by "supply chains," the most cited term with 267 citations, followed by "decision making" with 164 citations. The other members that appeared in the analysis are cost reduction, circular economy, industrial management, efficiency uncertainty, and health care. The major citing article of the cluster is Qui et al., 2024. The strong silhouette value denotes that the members of this cluster are closely related and well-grouped, reflecting a focused area of research within the broader field.

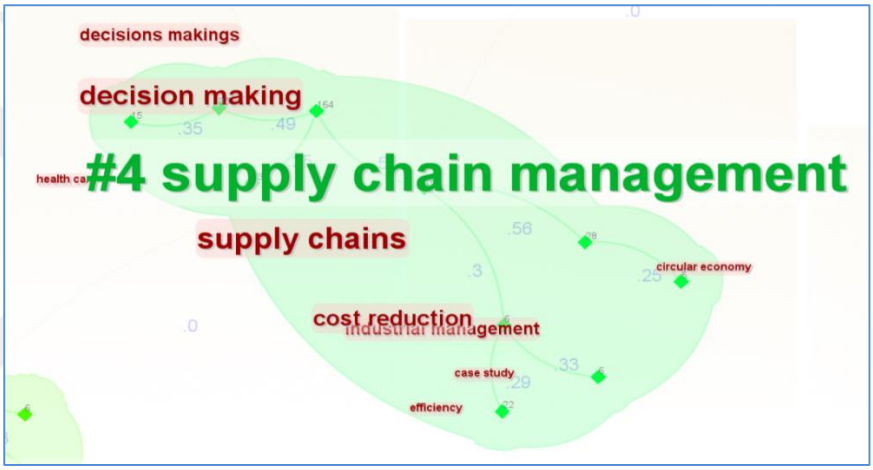


Figure 7. Keyword evolution across cluster #4.

2.2.1.6. Cluster 5

The title of this cluster is "secure blockchain. Its silhouette value is 0.977. This cluster, characterized by its focus on emerging technologies, features "Internet of Things" as the most cited member (100 citations), followed by "blockchain" (86 citations), and "artificial intelligence (AI)" (35 citations). Edhrabooh (2024) was the most-cited article in many clusters, including cluster 5. The high silhouette value expresses the relevance of the key concepts to each other within the cluster. This underlines the emergence of IoT, blockchain, and AI for secure applications. The focus of citations in the mentioned areas conveys their importance in secure blockchain technologies.

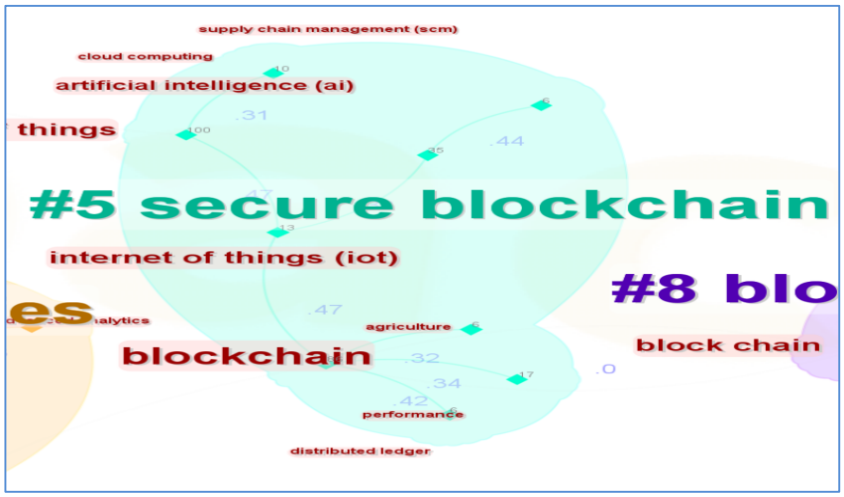


Figure 8. Keyword evolution across cluster #5

2.2.1.7. Cluster 6:

This cluster is named 'using soft computing. Its silhouette value of 0.903 proves that it follows an internal consistency. Within this cluster, 'industry 4.0' (53 citations) followed by 'competition' (38 citations), highlighting a clear emphasis on these concepts. The cluster score shows the related key terms. Zhang (2022) is also the most cited article for this cluster. This research explores soft computing's role in Industry 4.0 and the competitive landscape. Its silhouette value presents a meaningful clustering of the cited terms. Researchers are citing these topics a lot, which means they're really interested in how soft computing helps modern industries improve and compete.



Figure 9. Keyword evolution across cluster #6

2.2.1.8. Cluster 7

This cluster explains the integration of AI and ML into supply chain risk management. It exhibits a strong silhouette value of 1, indicating high internal consistency, and comprises eight members, consistently associated with supply chain risk management, decision support systems, and IoT information platforms. The primary citing article, Edhrabooh (2024), which has garnered significant citations, offers a systematic literature review of AI and ML applications within this field. The keywords "information management" and "risk management" appear with high citation frequencies, 79 and 59, respectively, within Cluster #7. This suggests a central focus of the cluster on the identification, evaluation, and mitigation of potential supply chain disruptions.

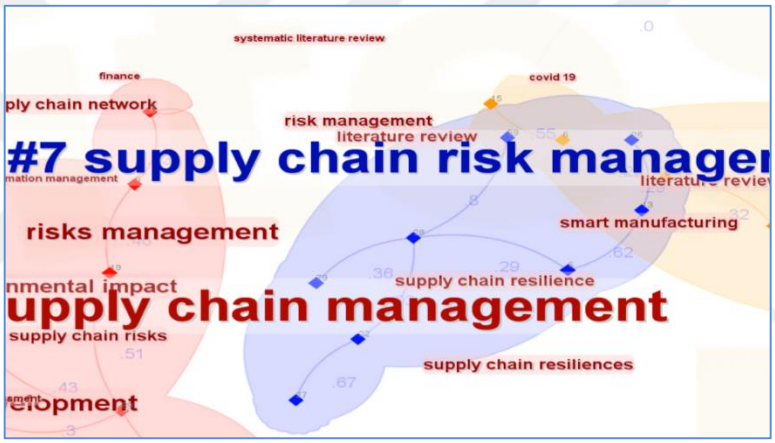


Figure 10. Keyword evolution across cluster #7

2.2.1.9. Cluster 8

The silhouette value of this cluster is 1, and it has six members. It reveals a real focus on blockchain applications, notably within supply chain contexts. The cluster exhibits strong associations with "supply chain management" and, to a lesser extent, "supply chain finance systems." The primary citing article, Chiranjeevi et al. (2021), underscores this focus by exploring blockchain technology's implementation in agricultural product supply chains. The high citation counts for terms such as "blockchain" (69), "food supply" (33), and "digital storage" (29) demonstrate that blockchain application for enhanced transparency, traceability, and data management within supply chain operations plays a key role.

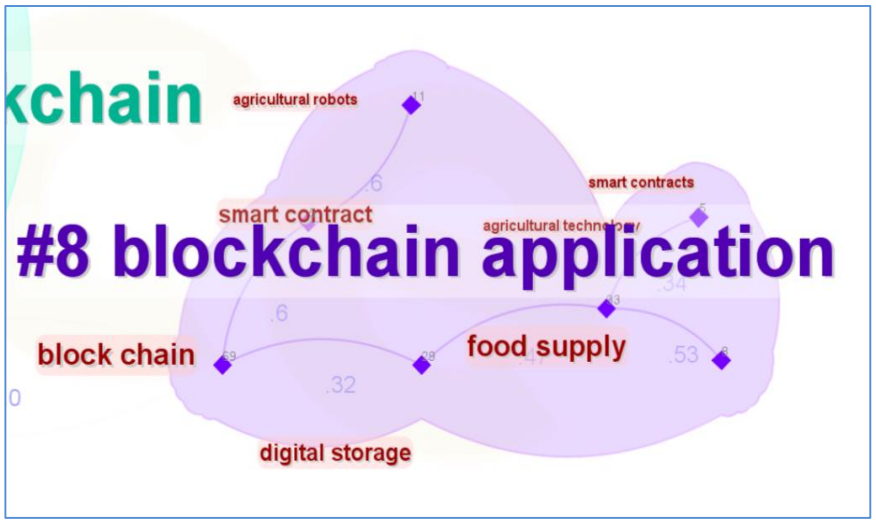


Figure 11. Keyword evolution across cluster #8

2.2.1.10. Cluster 9

This cluster has a silhouette value of 0.899. It holds five members. The cluster concentrates on demand forecasting. Its major citing article, Edhrabooh (2024), informs AI and ML applications within supply chain management, a field where accurate demand forecasting is crucial. With citation counts of 35 for "forecasting," 31 for "sales," and 21 for "demand forecasting," the cluster's focus on predicting future demand and optimizing related processes is clear.

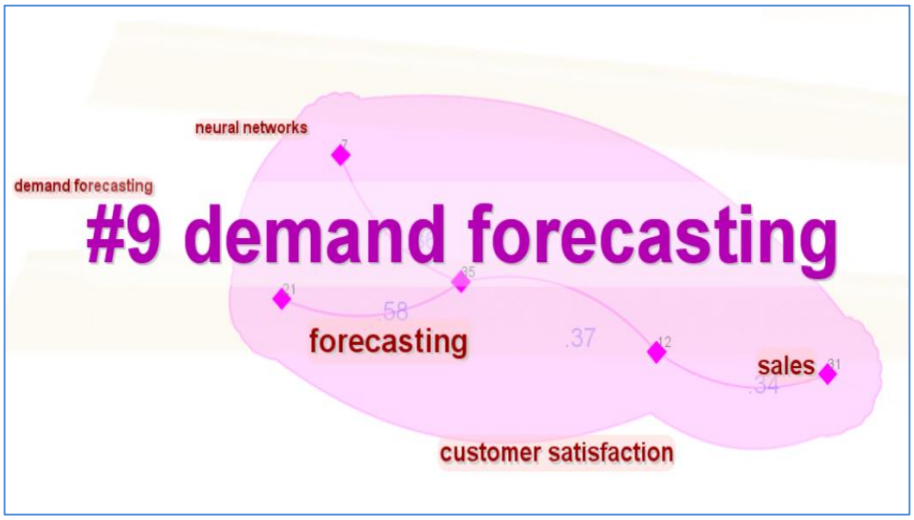


Figure 12. Keyword evolution across cluster #9

Table 2. Major clusters, including sizes, silhouette value, nodes, and average years

Cluster-ID	Size	Silhouette value	Node	Average Year
0	12	0.947	Sustainable supply chain management	2022
1	11	0.941	Smart technologies	2020
2	9	0.945	Deep learning approaches	2022
3	11	1	Decision support system	2022
4	9	0.958	Supply chain management	2021
5	8	0.977	Secure blockchain	2021
6	7	0.903	Using soft computing	2021
7	8	1	Supply chain risk management	2021
8	6	1	Blockchain application	2021
9	5	0.899	Demand forecasting	2021

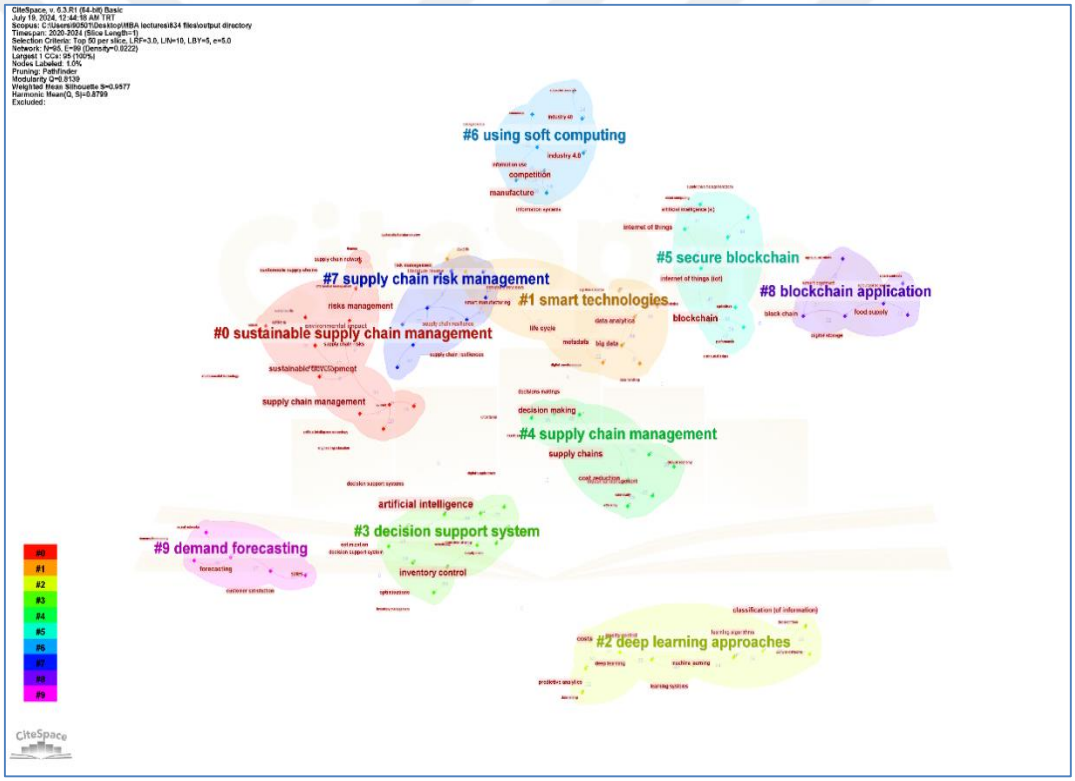


Figure 13. Keyword evolution across clusters

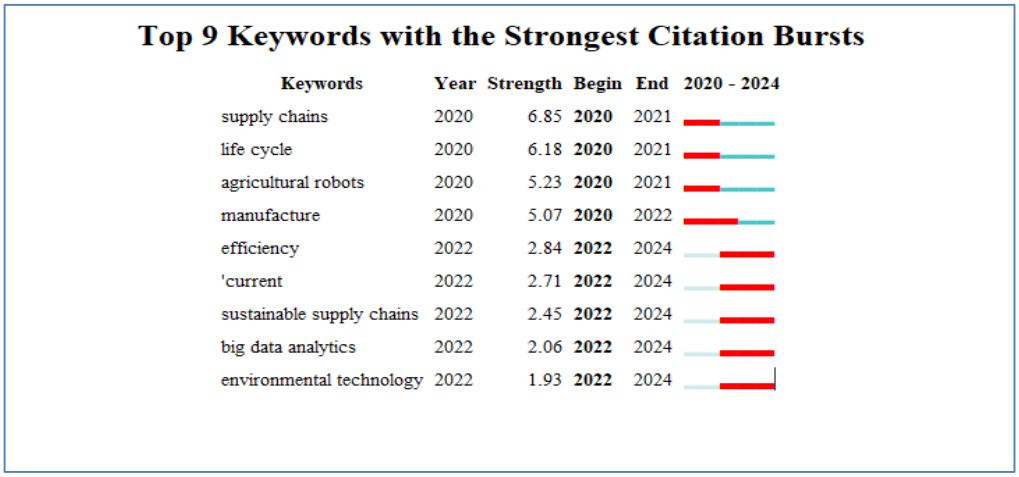


Figure 14. Citation counts and the burst of critical terms. Strength shows the total weight of links connected to that node.

2.2.2. Authorship and Collaboration

Analyzing authorship and collaboration in the field of artificial intelligence (AI) in supply chain management uncovers vast collaboration patterns among key authors and countries. The network analysis signifies three pivotal clusters of research activity.

2.2.2.1. Cluster 0

The largest cluster, classified as "supply chain network," consists of fundamental contributions from countries such as India, China, Germany, and the United States, the top three citation counts, with India leading at 187 citations. The cluster has nine members and a silhouette value of 0.811. This cluster's importance demonstrates substantial stress on AI's effect in improving supply chain networks, with key contributions from the study by Ali et al. (2024) on AI's implications for supply chain sustainability published in the Sustainability Journal. Visual representations of these clusters (Figure 15) visualize the clusters and illustrate the network of collaborations and citation impacts.

2.2.2.2. Cluster 1

The second largest cluster, recognized as "manufacturing supply chain," attracts attention to substantial contributions from the United Kingdom, France, and Morocco, with France being particularly influential, evidenced by its highest degree of centrality

(0.651) and citation impact (77 citations). This cluster emphasizes the merger of AI in manufacturing and retail operations. This insistence is supported by core publications such as the work by Arunmozhi (2022) on blockchain and smart contracts in independent vehicle supply chains. The collaboration between these countries underscores the cross-national efforts to merge AI technologies in diverse manufacturing contexts. Table 3 illustrates the citation counts, and Table 4 explains the centrality and details of Authorship and Collaboration. It highlights the cooperation of the main participants.

2.2.2.3. Cluster 2

The third cluster, termed "Enabling efficiency," demonstrates coordinated work from countries like Saudi Arabia, Australia, and Jordan. It concentrates on AI-supported data unification methods. Hussien et al. (2023) work on neural CSI feedback illustrates the advancements in this area. While this cluster is small in size, it concentrates on data consolidation and explains its key impact on rising supply chain management.

Table 3. Citation Counts of Authorship and Collaboration

Cluster-ID	Node Name	Citation Counts
0	India	187
0	China	116
0	United States	104
1	United Kindom	77
1	France	64
0	Germany	42
1	Morocco	38
1	Italy	36
2	Saudi Arabia	30
2	Australia	22

Table 4. Centrality details of Authorship and Collaboration

Cluster-ID	Node Name	Centrality
1	France	0.65
1	United Kingdom	0.62
0	India	0.26
0	Germany	0.20
0	China	0.20
0	United States	0.18
1	Pakistan	0.17
2	Canada	0.14
2	Jordan	0.13
1	Italy	0.12

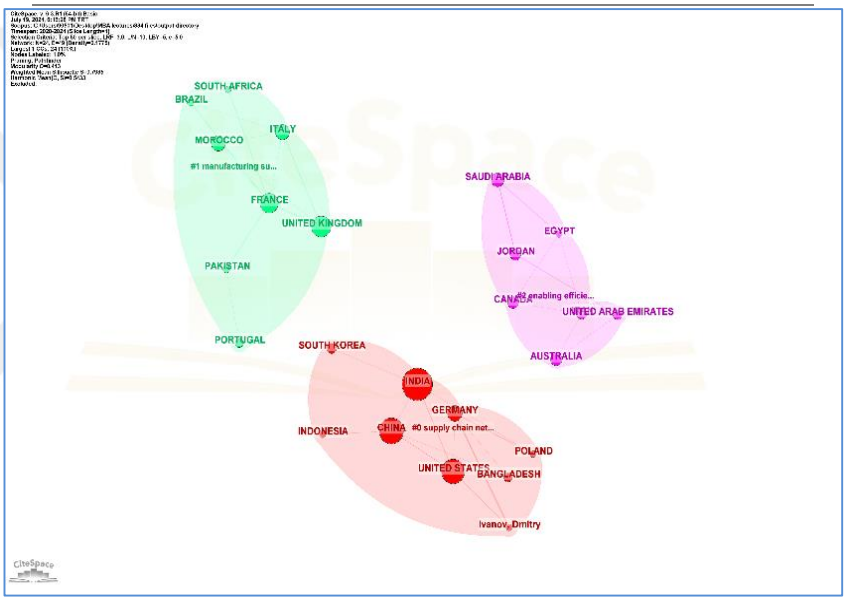


Figure 15. Cluster interconnectedness

2.2.3. Citation Analysis

The citation analysis revealed four significant clusters underlining influential papers and authors in AI in the SCM field from 2020 to July 2024.

2.2.3.1. Cluster 0

The first major cluster, identified as a capability-based framework, focuses on the role of generative artificial intelligence in supply chain and operations management. It consists of five members and has a silhouette value of 0.842, indicating a well-defined cluster. The primary citing article is by Jackson et al. (2024), which

presents a framework for analyzing and implementing AI in supply chain management. Key cited references include Ivanov & Dolgui (2020), with 12 citations, which examines the resilience of supply networks during the COVID-19 outbreak; Dubey et al. (2021), with six citations, which explores data analytics capability and organizational flexibility in supply chain resilience; and Ivanov (2023), which introduces intelligent digital twins for stress-testing supply chains. This cluster highlights the importance of AI-driven capabilities in enhancing supply chain resilience and adaptability.

2.2.3.2. Cluster 1

The second central cluster focuses on the integration of artificial intelligence in supply chain management. It also comprises five members, with a silhouette value of 0.691. The primary citing article is by Hao & Demir (2024), which examines AI's role in the pre-development, deployment, and post-development stages of supply chain management. Among the most cited references are Baryannis et al. (2019), with 34 citations, which discusses AI applications in supply chain risk management; Dubey et al. (2020), with 10 citations, which investigates big data analytics and AI's impact on operational performance; and Baryannis et al. (2019) with eight citations, which evaluates machine learning techniques for predicting supply chain risks. This cluster underscores AI's transformative impact on supply chain management, particularly in risk assessment and operational performance enhancement.

2.2.3.3. Cluster 2

The third cluster, labeled as key benefits in supply chain management, consists of four members with a high silhouette value of 0.937. Notable cited works include Toorajipour et al. (2021), with 25 citations, which provides a systematic review of AI applications in supply chains; Pournader et al. (2021), with 10 citations, which discusses various AI-driven applications in supply chain management; and Olan et al. (2022), which examines AI networks' role in sustainable supply chain finance. This cluster highlights the key benefits of AI in supply chain operations, including efficiency, automation, and enhanced decision-making.

2.2.3.4. Cluster 3

The fourth cluster centers on systematic literature reviews of artificial intelligence in supply chain performance. This cluster has five members and a silhouette value of 0.771. The primary citing article is by Zamani et al. (2023), which reviews the role of AI and big data analytics in building resilient supply chains. The most cited references include Cavalcante et al. (2019), with eight citations, which presents a machine learning approach for resilient supplier selection; Ivanov et al. (2019), with six citations, which assesses the impact of digital technology on supply chain risk; and Ivanov (2020) with six citations, which models the effects of epidemic outbreaks on global supply chains. This cluster highlights the growing body of literature analyzing AI's contribution to improving supply chain resilience and efficiency.

Table 5. Summary of the four most significant clusters.

Cluster-ID	Silhouette	Node	Average year
0	0.842	Capability-based framework for operations management	2021
1	0.691	Supply chain and artificial intelligence	2019
3	0.771	Systematic literature review	2019
2	0.937	Key benefit	2021

Table 6. Citation counts.

Cluster-ID	Node name	Citation Counts
1	Baryannis G	34
2	Toorajipour R	25
0	Ivanov D	12
2	Poirnader M	10
1	Dubey R	10
3	Cavalcante IM	8

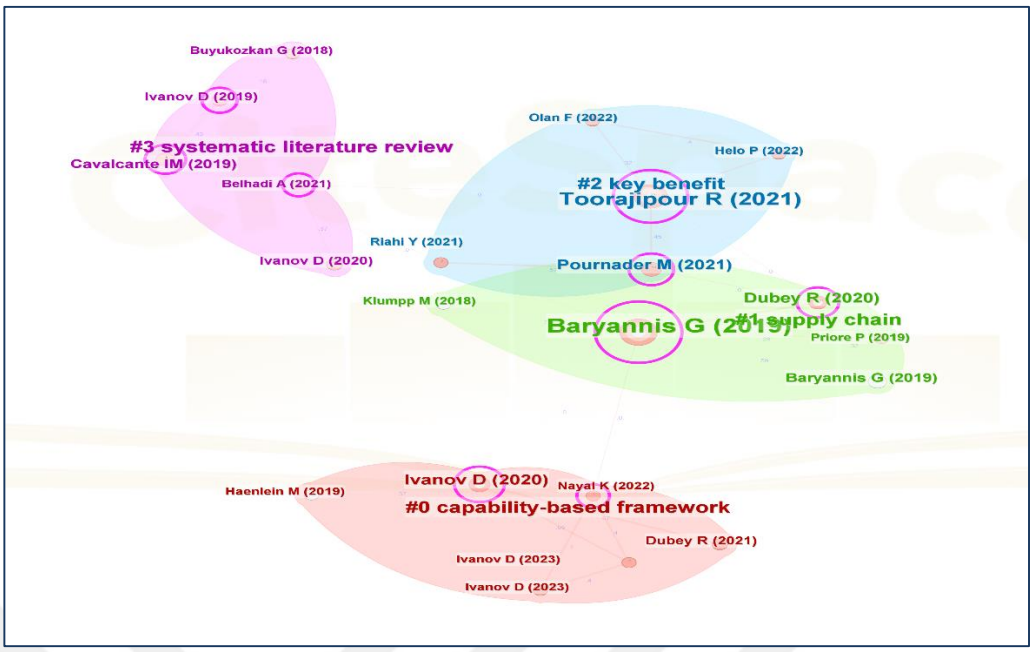


Figure 16. Network map of citation analysis

2.2.4. Co-Citation Analysis

The co-citation analysis performed using CiteSpace software uncovered nine remarkable clusters that mirror the research field within AI on SCM, especially in logistics and inventory management. Five valuable clusters were outlined as follows. These clusters offer opinions on the widespread research themes and influential works. A network diagram of these clusters is depicted in Figure 22.

2.2.4.1. Cluster 0

This cluster, as the largest, is centered around the theme of "sustainable smart cities" and underscores vital papers such as Tian et al. (2024), which discusses the role of "Datafication" (Data standardized and captured via IoT devices, is then processed using AI) in developing supply chain resilience and performance (Tian et al., 2024). The top cluster, "sustainable smart cities" (Cluster 0), has a silhouette value of 0.633. This cluster underscores the merging of AI in creating intelligent supply chains within the context of urban sustainability. This cluster has 17 members; the most cited works are by Belhadi et al., 2022. The above-mentioned clusters and their attributes, silhouette values, and labels are listed in Table 7.

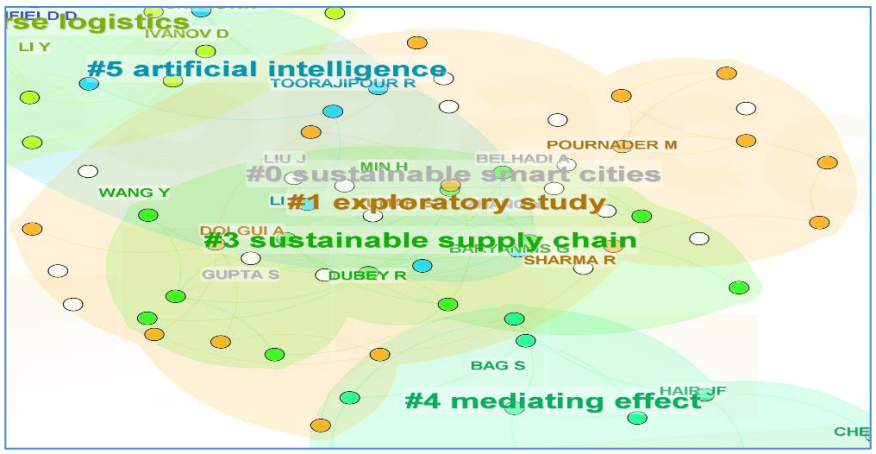


Figure 17. Network map of cluster #0.

2.2.4.2. Cluster 1

The exploratory study, or cluster 1, suggests that AI can play a useful role in food waste transformation processes. It is labeled as an exploratory study on artificial intelligence and food waste transformation. The major citing article of this cluster is also Tian et al., 2024. The most cited members are Sharma, Dolgui, and Kumar. The prominence of these subjects emphasizes the substantial implementation of AI in the SCM field. They encompass areas like the optimization of urban logistics and the management of sustainability in food supply networks. A network diagram of this cluster is depicted in Figure 18.

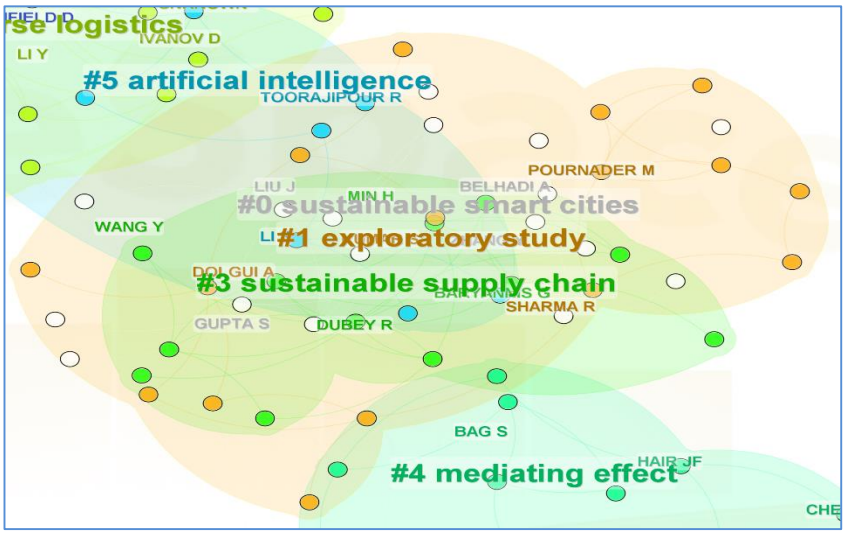


Figure 18. Network map of cluster #1

2.2.4.3. Cluster 2

This cluster represents reverse logistics and emerged as the third largest cluster with 13 members and a strong silhouette value of 0.702, indicating well-defined cluster boundaries. It is labeled as "reverse logistics," with a score of 2.34. The major citing article within this cluster is Singh (2024), focusing on building artificial intelligence-enabled resilient supply chains. Ivanov (117 citations), an unidentified source (74 citations), and Govindan & Hasanagic 2018 (52 citations) are the most cited members of this cluster. It suggests the significant influence of these authors and their work within the domain of reverse logistics and their intersection with AI and intelligent supply chain management.

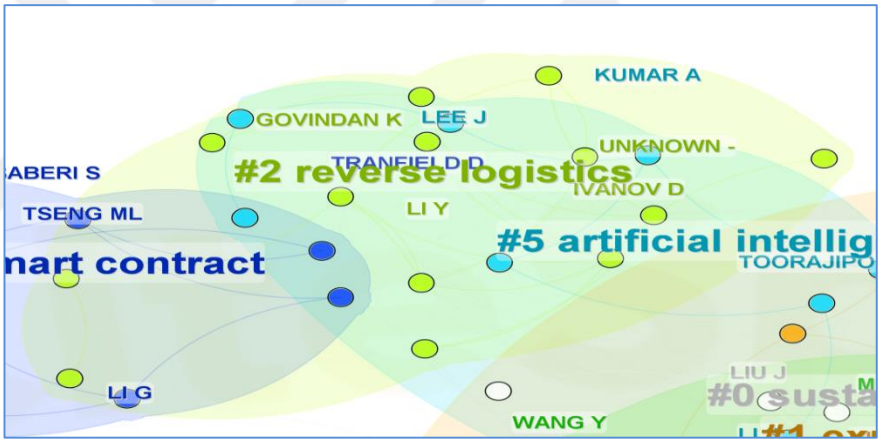


Figure 19. Network map of cluster #2.

2.2.4.4. Cluster 3

This is the fourth-largest cluster and is identified as a "sustainable supply chain," with a score of 1.63. It has twelve associates and carries a silhouette value of 0.969. The cluster's major citing article is Cadden, T. (2022), focusing on the influential and mediating role of cultural enablers in AI integration within the supply chain. Dubey R (78 citations), Baryannis G (71 citations), and Min H (69 citations) are the key contributors to this cluster. This group underlines the theoretical improvements of receiving knowledge regarding AI's effect on efficiency and sustainability in SCM

practices. They also highlight how technology integrates and helps sustainable supply chains.

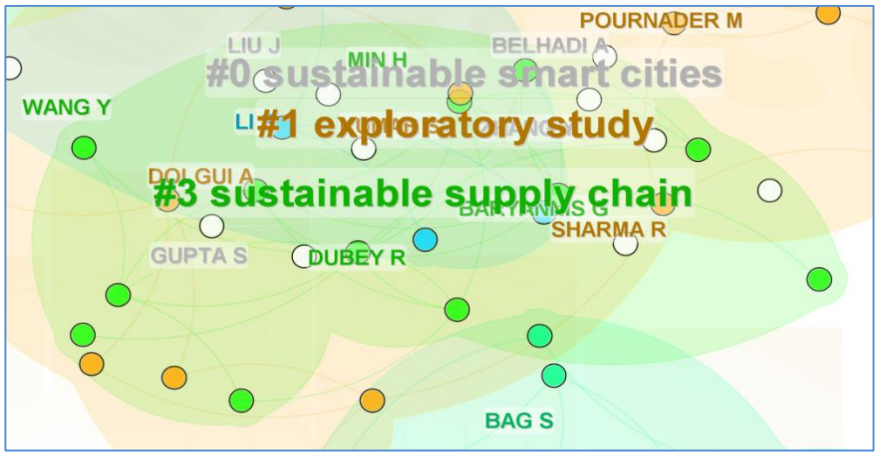


Figure 20. Network map of cluster #3

2.2.4.5. Cluster 4

This cluster is represented as the "mediating effect" with a lower score of 0.66. It contains 11 members and displays a strong silhouette value of 0.82. The values are the signs of good cluster cohesion. The major citing article for this cluster is again Cadden, T. (2022), which explores the influential and mediating role of cultural enablers in AI integration within the supply chain. Bag S (59 citations), Dwivedi YK (48 citations), and Hair JF (26 citations) are the main contributors to Clusterer 4. Their meaningful contributions to this cluster assist in understanding mediating effects within the context of supply chain research and related technologies.

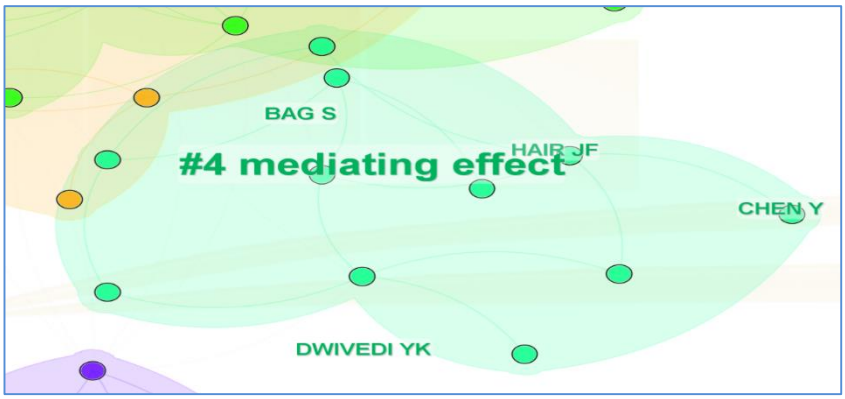


Figure 21. Network map of cluster #4

The co-citation analysis showed that foundational theories in SCM are being expanded through AI applications. The network map in Figure 22 emphasizes how the theoretical frameworks in this cluster are connected. Table 9 lists important conceptual contributions and explains what they mean for practice.

Note: The visual analysis revealed four more clusters: artificial intelligence, smart contracts, practice view, and artificial intelligence-based inventory management. However, the details of these clusters did not appear in the illustrations.

Table 7. Summary of the five most significant clusters

Cluster-ID	Silhouette	Label	Average year
0	0.633	Sustainable smart cities	2020
1	0.857	Exploratory study	2020
2	0.705	Reverse logistics	2020
3	0.969	Sustainable supply chain	2020
4	0.82	Mediating effect	2020

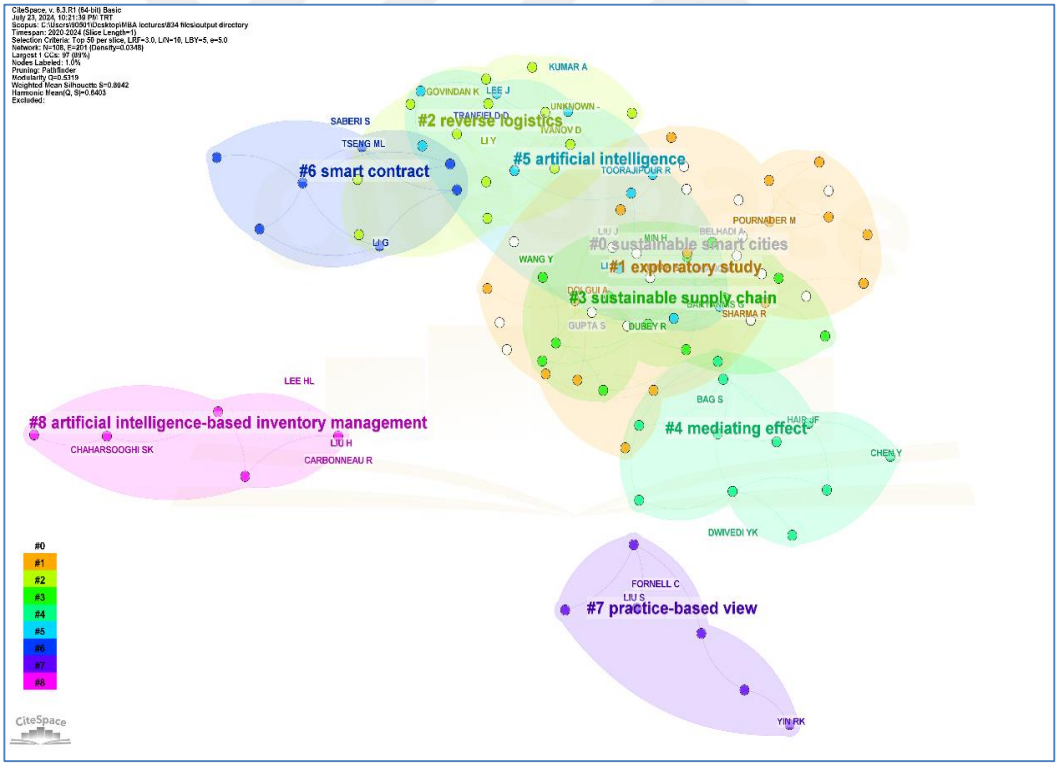


Figure 22. Network map of clusters

Table 8. Citation counts

Cluster ID	Node Name	Citation Counts
2	IVANOV D	117
3	DUVEY R	78
2	UNKNOWN	74
3	BARYANNIS G	71
3	MIN H	69
4	BAG S	59
5	TOORAJIPOUR R	54
3	WANG Y	53
2	GOVINDAN K	52
0	BELHADI A	51

Table 9. Key Conceptual Contributions and their applications

Key conceptual contributions	Primary authors/work	Application in Supply Chain Management	Impact Significance
Sustainable smart cities	Belhadi et al., Liu et al., Gupta et al.	Integrating AI for Datafication to enhance resilience and performance in manufacturing supply chains.	Promotes sustainability and innovation in smart city supply chains.
Exploratory study	Sharma et al., Dolgui et al., Kumar et al.	Applying AI to explore and transform food waste management in supply chains.	Reduces waste and improves sustainability in food supply chains.
Reverse logistics	Ivanov et al., Govindan et al.	Leveraging AI to enhance resilience and efficiency in reverse logistics.	Improves the efficiency of returns and recycling processes.
Sustainable supply chain	Dubey et al., Baryanis et al., Min et al.	Implementing AI within a 7-element digital twin framework for supply chain sustainability	Enhances sustainability and operational efficiency in supply chains.
Mediating effect	Bag et al., Dwivedi et al., Hair et al.	Utilizing AI to understand cultural enablers and their mediating effects on supply chain integration.	Enhances the integration and performance of AI in supply chains.

2.2.5. Thematic Mapping

The thematic mapping analysis using CiteSpace informed five significant clusters within the literature on artificial intelligence (AI) and supply chain management (SCM) from 2020 to Q1 2024.

2.2.5.1. Cluster 0

The most central cluster, identified as Cluster 0, focuses on "supply chain risk management" (Deiva, 2022). The mentioned cluster emphasizes the key impact of AI in avoiding or managing risks linked with supply chains. It is primarily done via improved decision-making processes and the deployment of decision support systems. The cluster's value is underlined by its citation counts, with "supply chains" cited 267 times and "decision making" 164 times (see Table 10 for detailed cluster statistics). The thematic map of this cluster (Figure 23) visually proves the dense interconnections and centrality of critical nodes such as "artificial intelligence" and "supply chain management."

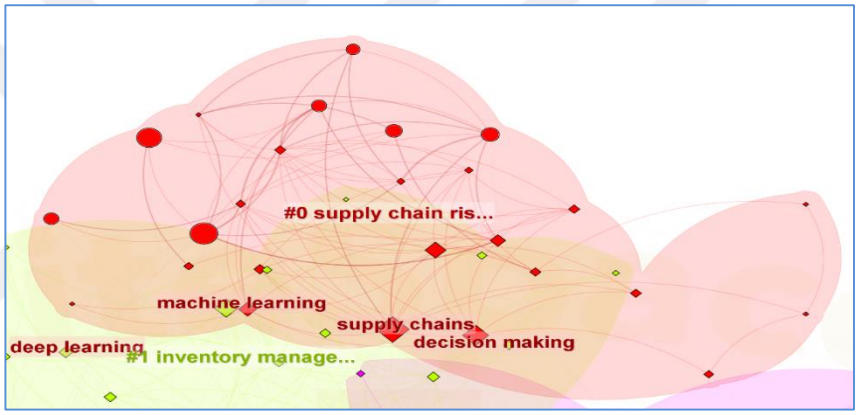


Figure 23. Interconnections among nodes in cluster #0

2.2.5.2. Cluster 1

This cluster is tagged "inventory management" and focuses on the economic and operational efficiencies of AI that are conveyed to SCM. The primary citing article by Mahat et al. (2023) stresses AI-driven optimization techniques that meaningfully improve inventory control and decrease operational costs. Essential terms within this cluster enclose "machine learning" and "deep learning," with citation counts of 137 and 40 (Table 11), respectively. This cluster's superiority is also imaged in its high silhouette value of 0.771, meaning well-defined and different research topics. The degree of centrality determines the number of links a node has with other network

nodes. Table 12 illustrates the centrality metrics of the leading publications in this cluster and supports the quantitative analysis.

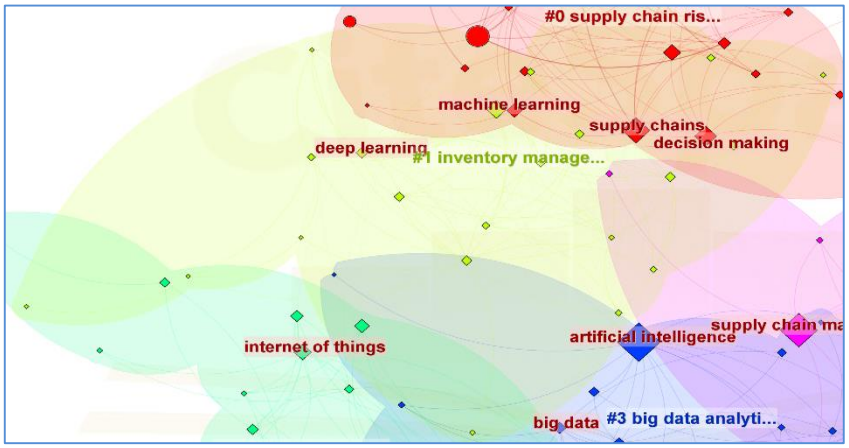


Figure 24. Interconnections among nodes in cluster #1

2.2.5.3. Cluster 2

This cluster was determined as the "smart city supply chain," which defines the merging of AI within the broader context of smart cities. This cluster underscores theoretical frameworks investigating the harmony between AI technologies, similar to the Internet of Things (IoT) and blockchain, within SCM (Chauhan et al., 2022). The main nodes of cluster 2 hold high citation counts of 100 and 86, respectively. They notify of the necessity of the mentioned nodes. Tables 10 and 11 explain it further. The thematic map (Figure 25) visually displays the interlinkage and centrality of these technologies within the cluster. It stresses their effect in developing the efficiency and transparency of supply chains in urban settings.

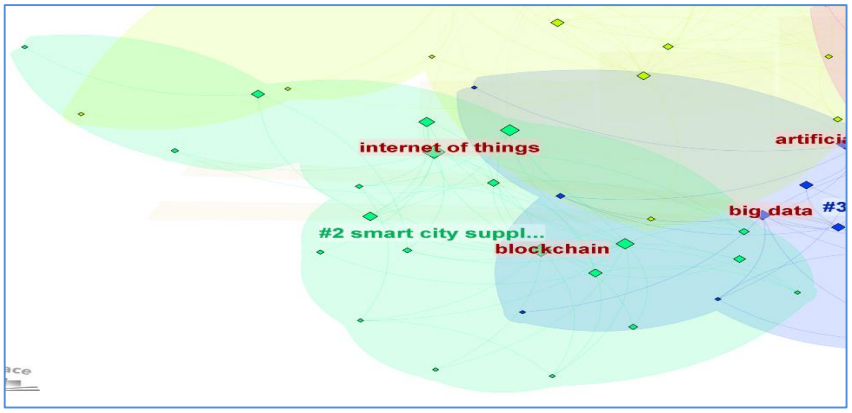


Figure 25. Interconnections among nodes in cluster #2

2.2.5.4. Cluster 3

This cluster is labeled "big data analytics" and discusses the challenges of implementing AI in SCM. The primary citing article by Kunkel et al. (2022) debates the complexities of integrating big data analytics with AI to optimize supply chain processes. This cluster includes highly cited nodes like "artificial intelligence" (682 citations) and "big data" (59 citations), indicating the important academic interest and practical challenges in this area. The high betweenness centrality of these nodes mirrors their pivotal role in bridging miscellaneous subfields within the cluster.. Figure 26 describes the thematic map, showing the dense network of interrelated concepts and the centrality of big data analytics.

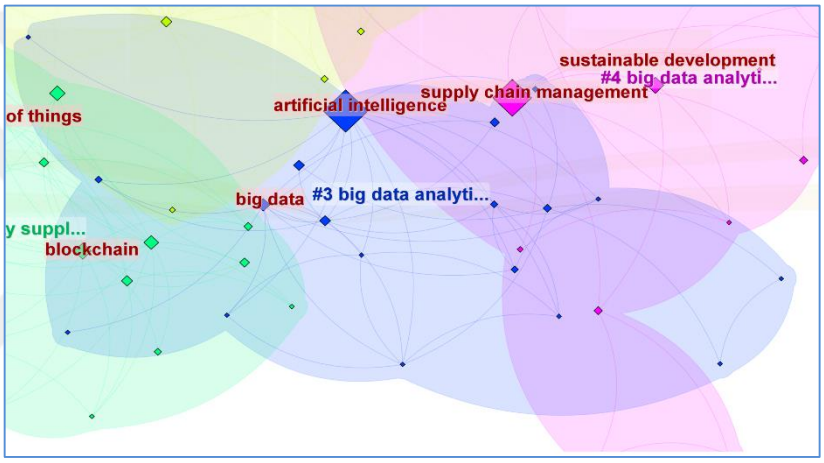


Figure 26. Interconnections among nodes in cluster #3

2.2.5.5. Cluster 4

This cluster is also centered on "big data analytics," but concentrating on sustainable development emphasizes AI's dual role in improving supply chain efficiency while promoting sustainability (Habib & Hwang, 2024). This cluster comprises nodes including "supply chain management" (486 citations) and "sustainable development" (89 citations), underscoring the rising concentration on sustainable methods in SCM supported through AI systems. The prospects in this cluster are crucial for knowing the balance between operational efficiency and environmental responsibility in modern supply chains. Table 11 lists details about the top ten citation counts.

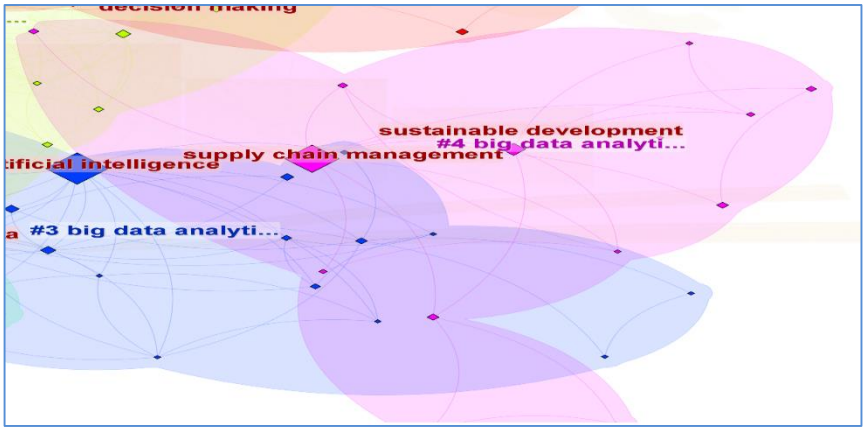


Figure 27. Interconnections among nodes in cluster #4

Table 10. Detailed cluster statistics.

Cluster ID	Size	Silhouette	Label	Average Year
0	37	0.672	Blockchain Power Trading	2022
1	30	0.639	Decision Support System	2021
2	30	0.788	Mediating role	2021
3	27	0.86	Decision Support Systems	2021
4	27	0.849	Demand Forecasting	2022

Table 11. Citation Counts

Cluster ID	Node Name	Citation Counts
1	Artificial intelligence	682
3	Supply Chain Management	486
3	Supply Chains	267
3	Decision Making	164
4	Machine Learning	137
0	Internet of Things	100
3	Decision Support Systems	99
1	Sustainable Development	89
0	Blockchain	86
2	Supply Chain	80

Table 12. Centrality.

Cluster ID	Node Name	Centrality
1	Artificial Intelligence	0.34
3	Supply Chains	0.25
3	Supply Chain Management	0.22
2	Supply Chain Risk Management	0.16
0	Internet of Things	0.11
0	Digital storage	0.11
0	Block Chain	0.10
1	Big Data	0.10
0	Blockchain	0.09
1	Sustainable Development	0.08

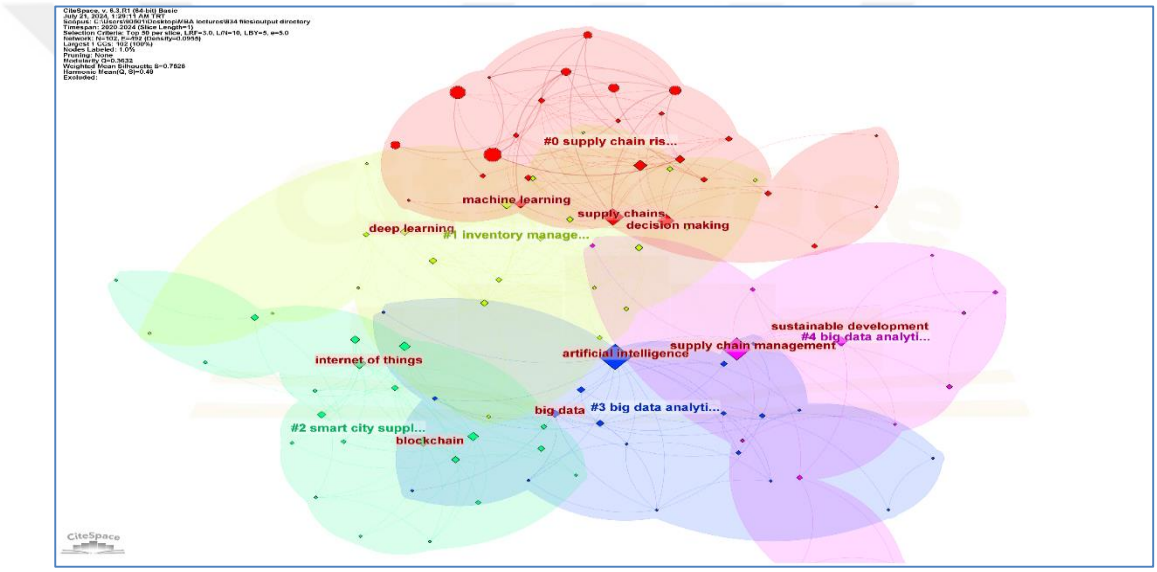


Figure 28. Interconnections among nodes (specifically between AI and SCM)

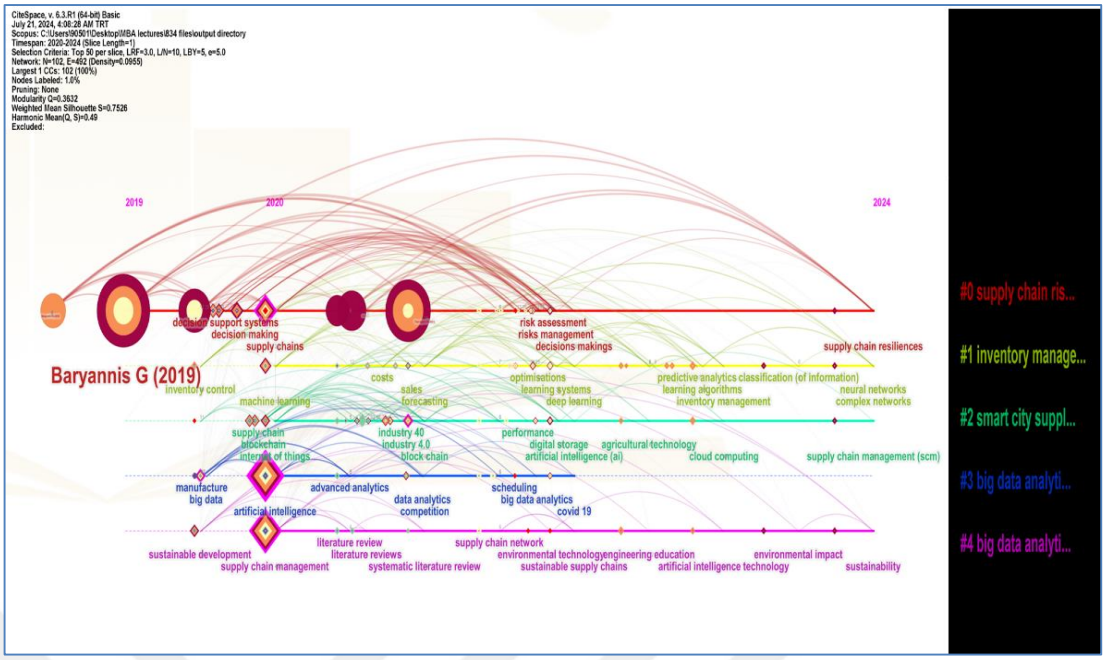


Figure 29. Interconnectedness of clusters over a timeline view

2.2.6. Key metrics and insights

Important metrics and insights: Through all clusters, several core metrics, including citation counts, degree centrality, and betweenness centrality, spotlight the importance and effect of particular topics and academic publications. For example, 'artificial intelligence' is continuously rising as a central node throughout several clusters. The topic has the topmost centrality (57) and citation counts (682). The substantial appearance of the mentioned topic reaffirms AI's underlying impact on SCM research. Likewise, the idea of 'supply chain management' shows high centrality and citation counts. Clusters 4 and 0 emphasize the importance of SCM in the notion of AI applications. The centrality metrics (see Table 12) provide further quantitative evidence of the interconnectedness and impact of these core concepts across the thematic landscape. In Figure 29, references are demonstrated as overlays on a timeline view. Clusters are displayed horizontally and advance through time from left to right.

CONCLUSION AND RECOMMENDATIONS

This thesis offers a holistic bibliometric analysis of the impact of AI on SCM from 2020 to the 1st quarter of 2024, focusing on logistics and inventory management. This study illustrates the evolution of publication trends, the geographical distribution of research contributions, critical journals and conferences, emerging topics and trends, and citation analysis of influential papers, authors, and institutions, utilizing data from the Scopus database. The data visualization process was conducted using CiteSpace software, as presented in the above figures.

Summary of Findings

The study underlined a considerable expansion in research concentrated on AI in SCM. It shows the intensified effectiveness and acknowledgment of AI technologies in upgrading supply chain processes. Incorporating AI into supply chain management has developed the overall process, particularly logistics optimization and inventory management. Efficiency, responsiveness, and competitiveness in supply chain practices will be achieved through the mentioned approach.

Geographically, the research cooperation is mainly from well-developed countries like the United States, China, and India. They mark a world-level interest in the deployment of AI in SCM processes. The mentioned geographical cooperation stresses the collaborative characteristics of research in this field. It shows the global relevance of AI-based supply chain innovations.

Key Research Themes

The bibliometric analysis specified several key research themes. One known theme is the function of AI in sustainable supply chains, especially in the context of smart cities and food waste management. The work has demonstrated the way AI can develop sustainability. As an example, AI-based systems can strengthen source efficiency and minimize waste.

Another meaningful topic is the benefit of AI in reverse logistics, which focuses on product recovery and recycling. The work has revealed through what method AI

advances effectiveness and resilient all the way to reverse logistics processes. It directs to an endurable and budget-friendly supply chain.

Influential Authors and Papers

With the help of citation analysis, prominent authors and papers that have contributed to AI-SCM-related studies were listed. Ivanov, Dubey, and Baryannis are known contributors whose studies have delivered fundamental theories and practical frameworks for implementing AI in supply chain operations. These contributions have been fundamental in increasing our understanding of how AI can force efficiency, resilience, and sustainability in supply chains and operations management, particularly during the COVID-19 pandemic. The author argues that on-time data monitoring and predictive analytics play a key role in organizational insistency. The improvement and utilization of research outcomes is the job of practitioners.

Conceptual Contributions

The co-citation analysis underscored the theoretical and conceptual contributions that have constructed the current research landscape. Pivotal conceptual models comprise the integration of AI in digital twin frameworks, which improve operational efficiency and sustainability, and the investigation of mediating effects, such as cultural promoters, in AI utilization within supply chains. These models present valuable opinions on the thorough effect of AI on SCM. The models also connect the two sides of theoretical development and applicable undertakings.

Limitations

Even though this study is holistic, it has limitations that need addressing. Because it only used the Scopus database, it likely missed related publications in other databases, which could narrow our understanding of the research landscape. The bibliometric analysis mainly focuses on quantitative measures, which may only partially grasp the qualitative aspects of research impact and innovation. Similar restrictions tell us that there is a need to combine different data sources and methodologies for future studies.

Subsequent Research Opportunities

Investigating the qualitative effects of AI on SCM—specifically its impact on personnel behavior, workplace culture, and decision-making processes—could offer valuable insights into these aspects.

Research should also investigate how AI employment will affect the long-term sustainability and resilience of supply chains, especially when it comes to challenges like climate change and geopolitical tensions.

Similarly, interdisciplinary research that connects opinions from AI, SCM, and related domains, including environmental science and economics, can demonstrate a broader perspective on AI's potential and limitations in converting supply chains. Collective efforts among academia, industry, and policymakers are not just important but vital to driving innovation and guaranteeing the successful adoption of AI technologies in supply chains.

Summary

At the end, this thesis has delivered a detailed bibliometric analysis of the impact of AI on SCM, underlining significant research trends, influential contributions, and critical themes from 2020 to 1Q 2024. Data was retrieved from the Scopus database, and the visualization process was performed using CiteSpace software. The results stress the revolutionary capacity of AI in advancing supply chain operations. AI can foster sustainability. However, limitations exist; the analysis gives useful opinions and sets the stage for future research directions, further exploration, and harnessing AI's advantages in SCM. Through continued research and cooperation, AI can play a pivotal role in designing the future of supply chains, making them more efficient, resilient, and sustainable.

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RESUME

Personal Information

Surname, Name: JALALI, FARID AHMAD

Nationality: Afghanistan

Education

Degree	Education Unit	Graduation Date
Master (MBA)	Gelisim University	**2025**
Bachelor (BCS)	Kardan University	**2019**
High School	Afghanistan Institute of Technologies	**2002**

Work Experience

Year	Place	Title
2000 – 2004	Afghanistan	Volunteer worker, Supervisor, Trainer, and monitor for immunization programs
2004 - 2012	Afghanistan	The salesperson in Rahimi Car Showroom
2012 – 2020	Afghanistan	Executive Director At Shahan Ltd.
2022 - 2023	Turkey	Owner & Executive Director for Zowak Exports Ltd.

Foreign Language

Persian Pashto English Turkish

Hobbies: Reading books, Networking, Walking, Traveling