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"ARTIFICIAL INTELLIGENCE AND SUPPLY CHAIN MANAGEMENT: A LITERATURE REVIEW"

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Firma (signature) ………………………………………

Alla mia famiglia,

simbolo di amore e costanza

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ABSTRACT (in Italian)

Il presente elaborato si propone di analizzare l'affascinante ed intricata intersezione dei due campi dell'intelligenza artificiale (IA) e della supply chain (SC), in modo da esplorarne il potenziale impatto e chiarire come le organizzazioni possono sfruttare queste tecnologie. Gli ultimi progressi e le recenti rivoluzioni hanno infatti reso evidente le capacità ed i potenziali benefici di tali strumenti, sottolineandone l'indispensabile integrazione all'interno delle aziende che vogliono aumentare l'efficienza operativa ed ottenere un vantaggio competitivo. Questo fenomeno è particolarmente enfatizzato dalla crescente complessità nel gestire catene di fornitura in un ambiente commerciale sempre più competitivo, come dimostrato anche dalla recente pandemia di Covid-19. L'IA e le altre tecnologie emergenti possono dunque creare una simbiosi ottimale per il contesto odierno, portando numerosi benefici sia in termini di costo, produttività ed efficienza.

Nonostante il crescente interesse per l'argomento e la graduale implementazione di questi strumenti innovativi all'interno delle aziende, permane una carenza di ricerca fatta su questo fronte. Questo studio ha dunque l'obbiettivo di colmare alcune lacune esistenti nelle pubblicazioni disponibili ad oggi, esaminando 518 articoli di ricerca pubblicati tra il 1999 ed il 2023 dal database di Scopus. Il lavoro è strutturato come segue: Nel primo capitolo introduttivo vengono presentati i due concetti chiave dell'Intelligenza Artificiale e del Supply Chain Management. Nel secondo capitolo viene fornita una panoramica sull'importanza dell'intersezione di queste due aree e del come la letteratura corrente ha affrontato questo argomento. Il terzo capitolo è dedicato alla metodologia e spiega come è stato costruito il database di articoli e come è stato visualizzato ed analizzato tramite l'utilizzo del software VOSviewer e dell'analisi bibliometrica. Nel quarto capitolo vengono presentati i risultati della ricerca tramite l'analisi delle tre mappe create con l'apposito software. L'ultimo capitolo riporta le principali conclusioni derivabili da questo elaborato, rimarcando l'importanza dell'argomento trattato e sottolineando le limitazioni del presente studio, nonché le possibili direzioni per i ricercatori futuri.

ABSTRACT

This thesis aims to analyse the fascinating and intricate intersection of the two fields of artificial intelligence (AI) and supply chain (SC), in order to explore their potential impact and clarify how organizations can leverage these technologies. Recent advancements and revolutions have indeed highlighted the capabilities and potential benefits of such tools, underscoring their essential integration within companies seeking to enhance operational efficiency and gain a competitive advantage. This phenomenon is particularly emphasized by the growing complexity of managing supply chains in an increasingly competitive business environment, as demonstrated by the recent Covid-19 pandemic. AI and other emerging technologies can thus create an optimal symbiosis for the nowadays context, yielding numerous benefits in terms of cost, productivity, and efficiency.

Despite the growing interest in the topic and the gradual implementation of these innovative tools within companies, there remains a research gap in this area. Therefore, this study aims to fill some of the existing voids in the available literature, examining 518 research articles published between 1999 and 2023 from the Scopus database. The work is structured as follows: The first introductory chapter presents the two key concepts of Artificial Intelligence and Supply Chain Management. The second chapter provides an overview of the importance of these two areas and how the current literature has addressed this topic. The third chapter is dedicated to the methodology and explains how the database of articles was constructed and how it was visualized and analysed using the VOSviewer software and bibliometric analysis. The fourth chapter presents the research results through the analysis of the three maps created with the software. The final chapter outlines the main conclusions drawn from this paper, emphasizing the significance of the treated topic and highlighting the limitations of the present study, as well as suggesting potential directions for future researchers.

1. INTRODUCTION

With the latest advancements, the integration of emerging digital technologies has become indispensable for organizations seeking to gain a competitive edge. Among these revolutionary developments, the intersection of the two fields of artificial intelligence (AI) and supply chain (SC) stands out as a particularly impactful phenomenon, revolutionising traditional business practices and providing ample opportunities to increase operational efficiency.

The present, introductive chapter presents the two important concepts of “supply chain management” and “artificial intelligence”. Before delving into the actual discussion of the topic on which this thesis is centred, it is crucial to familiarize ourselves with these core fields in order to elucidate their key principles, functions, and strategic significance. By establishing a solid knowledge foundation, we will be well-equipped to examine these domains' convergence and uncover how AI can revolutionize supply chain operations.

1.1 WHAT IS SUPPLY CHAIN MANAGEMENT

Nowadays, the area of the supply chain is attracting growing attention because of the thriving complexity in managing networks of (very often global) business relationships in an increasingly more competitive business environment. Providing a general concept, we can identify a “supply chain” with the network of organizations, people, activities, information, and resources involved in the creation and delivery of a product or service from the supplier to the end customer (Bechtel and Jayaram, 1997; Christopher, 2016; Janvier-James, 2011). Mentzer et al. (2001, pg. 18) define supply chain management as “*the systemic, strategic coordination of the traditional business functions and the tactics across these business functions within a particular company and across businesses within the supply chain, for the purposes of improving the long-term performance of the individual companies and the supply chain as a whole*”. Thus, the broader objective of supply chain management is to enhance the efficiency and effectiveness of the supply chain in terms of cost, quality, responsiveness, and sustainability. It is important not to confuse this latter, more comprehensive concept, with the one of “logistics management”, which represents the part of SCM that “[…] *plans, implements, and controls the efficient, effective forward and reverses flow and storage of goods, services and related information between the point of origin and the point of consumption in order to meet customers' requirements*”, according to the Council of Supply Chain Management Professionals (“SCM Definitions and Glossary of Terms”, n.d., pg. 117).

To achieve the aforementioned objectives, an efficient supply chain management needs to handle three types of flow that also represent the key elements of a SC. The first one is the physical product flow, which refers to the movement of commodities from the producer to the final consumer via various middlemen such as wholesalers, distributors, and retailers and it is important for a firm's business to ensure effective and timely procurement and delivery. The information flow, on the other hand, relates to the exchange of data, information, and knowledge among the stakeholders of the supply chain. This includes information on demand, stock levels, manufacturing and delivery timetables, and other relevant metrics, and it is crucial for enabling coordination and communication between different parties, allowing them to work together more effectively. Finally, the financial flow regards the movement of money between the different players throughout the supply chain, such as suppliers, manufacturers, distributors, and retailers (Chopra and Meindl, 2016).
Regarding the last type of flow, it is important to highlight that the only source of revenue for a company comes from the customer, and the main objective of efficient SCM is the one of maximizing customer value. The success of the management is therefore measured by the supply chain surplus, which is given by the difference between the customer value and total costs of handling the SC (Mentzer et al., 2001).

1.2 WHAT IS ARTIFICIAL INTELLIGENCE

The term "artificial intelligence"[1] has gained more notoriety in recent years, even among non-specialists, and it now has a more precise definition and a different meaning than when it was initially coined by Alan Turing and other notable mathematicians in the 1950s (Turing, 2009). Despite not being simple to provide a complete and unique definition for this concept, in his paper John McCarthy (2007, pg. 2) defines AI as "[…] *the science and engineering of making intelligent machines, especially intelligent computer programs. It is related to the similar task of using computers to understand human intelligence, but AI does not have to confine itself to methods that are biologically observable.*" Two aspects of the previous definition are noteworthy and interesting. The first one is in the use of the word "artificial," which conjures images of constructions that are not derived naturally but rather from human hands. On the other hand, it is challenging to provide a clear definition for the term "intelligence," and although we frequently relate it with human intellect, AI's methods are not constrained by this comparison and frequently go beyond how human minds solve problems (Nilsson, 1998).

[1] From now on the concept "artificial intelligence", for simplification, will be used interchangeably with the other terms "AI", "smart technologies", and "digital technologies".

Inside the broader concept of AI, we find multiple branches and subgroups that very often identify with the different technologies applied within this scientific discipline to realize the objectives set in the previous definition. In this brief introduction I will just concentrate on the types that, in light of recent advancements, are currently garnering growing attention and are being utilised most widely. The first technology is “machine learning”, which is the subset of artificial intelligence that aims to learn from data and make predictions and/or decisions without being appositely programmed to do so. To simplify the concept, imagine you had to teach someone to recognise a certain breed of dog. You would probably show them pictures of different examples rather than trying to explain the exact characteristics that define that breed. In the same way, ML involves training computers to recognise and understand patterns and relationships by analysing large amounts of data, rather than simply programming them with specific rules. ML can be classified into “shallow” and “deep” (Enholm et al., 2022), but to clarify this distinction I first need to introduce another important and strongly related concept. “Neural Networks” is a notion inspired by biological systems and it represents a particular class of ML algorithms that consists of mathematical representations of connected processing units called “artificial neurons” (Janiesch et al., 2021). These neurons are frequently arranged into networks with several levels: an input layer receives the data input, and an output layer generates the final output. In between there can be zero or more hidden layers that are in charge of learning the non-linear input-to-output mapping, and here comes the concept of “Deep Learning”. Indeed. DL is the subset of machine learning (and consequently of artificial intelligence) that focuses on the study of artificial neural networks and related ML algorithms that contain more than one hidden layer (Ongsulee, 2017). Deep learning is therefore particularly advantageous in fields with large and high-dimensional data, making it a useful tool for applications that involve the processing of text, images, speech, and audio.

Given these points, it is worth highlighting that the evolution and advancement of the aforementioned and many other technologies (natural language processing, computer vision and speech synthesis systems just to name a few) and tools such as ChatGPT are a result of the expansion of data availability and the improvements in computing power (Haenlein and Kaplan, 2019).

2. LITERATURE REVIEW

So far, two very important and current topics have been presented, but recent research and studies made it clear that the intersection between the two is increasingly being considered a potential source of competitive advantage and, consequently, a disruptive force for many businesses. Artificial intelligence is indeed a fast-developing phenomenon with significant economic and organizational implications, and the notion of "AI capabilities" (Enholm et al. 2022, pg. 6) precisely refers to the organizational capacity of deploying such applications in support of operations. When these two domains are combined, multiple mutual benefits may be found, including gains in costs, productivity, and customer satisfaction in areas like demand forecasting, inventory level optimisation, logistics planning improvement, and many more (Kar and Kushwaha, 2021). Generally speaking, however, of the three flows previously described, the most influenced and improved one is undoubtedly the information stream, considering that digital technologies are particularly useful in enhancing the visibility and transparency of a supply chain.

Despite the growing interest and widespread implementation of these technologies in industry, there is still a paucity of work done regarding this topic. Given the continuous and rapid evolution of both artificial intelligence and supply chain management, it is fundamental to provide a new, more recent and updated systematic literature review. Being the analysis of the application of smart technologies in the SC at its early stages, there is no established framework or standardized approach to investigate the topic (Toorajipour et al., 2021), and therefore there are still important gaps in the studies of this field. The most relevant literature reviews (published in the last ten years) that are currently available are the ones of Ngai et al. (2014), Riahi et al. (2021), and Toorajipour et al. (2021). For instance, the study conducted by Ngai et al. (2014) has certain limitations in its approach as it only utilizes a subset of 77 papers that specifically focus on the sectors of textile production, apparel manufacturing, and distribution/sales. Regarding the other cited papers, as well as other significant contributions that are not directly referenced in my thesis, they tend to concentrate on narrower topics by conducting detailed analyses of smaller clusters of articles, thereby omitting important aspects. For these reasons, my research differentiates itself from the aforementioned studies especially in its methodology. By utilizing novel tools and employing a broader keyword scope, I had the opportunity to analyse a larger database of articles using bibliometric analysis through the VOS technique (Eck and Waltman, 2009). This approach is not commonly employed in existing systematic literature reviews.

However, it enabled me to gain a broader perspective on the applications of AI within the supply chain, encompassing the latest innovations, and make a more original contribution to scholarly research. The purpose of this thesis is, therefore, the one of exploring the weighty impact of artificial intelligence on SCM and how organisations can leverage AI-driven technologies to overcome challenges, improve responsiveness, and foster innovation within their supply chains (Grover et al., 2022).

This brief overview aims to grab the readers' interest and pique their curiosity while also bringing to light the complexity of the subject. This is especially clear when we put ourselves in the shoes of the decision-makers who must assess the investment in these cutting-edge technologies, while also considering the high costs that are associated with them and the long-term viability of the company.

3. METHODOLOGY

3.1 BIBLIOMETRIC ANALYSIS

In recent years, with the exponentially increasing number of available information, bibliometric analysis has become one of the most popular and used methods for analysing large volumes of scientific data. Bibliometric analysis can be defined as a quantitative method for analysing scientific literature, and it is based on citation counts, co-citation analysis, bibliographic coupling, and other bibliographic data. It is very useful to provide insights into patterns of research activity, intellectual connections between authors and papers, and the impact of research on a particular field (Van Raan, 2004).

As mentioned before, several techniques are used in this context to analyse scientific literature, particularly for science mapping, which refers to the idea of visualizing bibliometric networks (Van Eck and Waltman, 2014). The most basic one is citation analysis, which assumes that the impact of a publication is related to the number of citations it received. On the other hand, co-citation analysis assumes that papers that are often cited together are similar thematically and therefore is more helpful in revealing the underlying themes of a research field. The third technique, known as bibliographic coupling, differs from the previous one because it is based on the assumption that the thematic similarity and commonality of two or more publications is identified by the frequency they cite the same works. This type of analysis is therefore useful for providing a picture of the present of the research field.

Co-word analysis differentiates itself from the previous techniques because it uses as the unit of analysis the keywords of the papers. The underlying assumption of this type of analysis is that words that appear more often together probably have a thematic relationship with one another, and therefore it can provide a better understanding of the thematic clusters derived from the other techniques.
Finally, co-authorship analysis is used to investigate the frequency and patterns of collaboration among authors of scholarly publications, revealing their interactions in a research field. This can help identify the most influential authors and map collaborations across different periods to analyse the evolution of a particular cluster (Donthu et al., 2021).
For the purposes of my research, only the co-citation, bibliographic coupling, and co-word techniques were used.

3.2 CONSTRUCTION OF THE DATABASE

For the study of relevant publications and the construction of the subsequent database of articles, I used Scopus as research tool, which is an abstract and indexing database with full-text links produced by the global publisher of academic literature Elsevier Co. (Burnham, 2006). The research equation with the application of the Boolean operators and wildcard characters was: *"artificial intelligence" OR "ai" OR "digital technolog*" OR "collaborat* robot" AND "supply chain" OR "operations management" OR "supplier*" OR "purchasing" OR "logistics" OR "transportation" OR "production" OR "*sourcing" OR "distribution" OR "inventor*".* This search, with the selected year range 1999 – 2013, gave a first result of 68,225 documents found.
With the obtained result, I started the filtering phase by applying specific quality criteria to screen the relevant papers. By including only English-written articles from academic and trade journals in the subject areas of “Business, Management and Accounting”, “Economics, Econometrics and Finance” and “Decision Sciences”, the research narrowed down to 2,973 documents found. Finally, I consulted the *Chartered ABS Journal Guide (2018)* and chose only the major journals (with a ranking of 3 or 4 stars) in the fields of “Ethics, CSR and Management” (ETHICS-CSR-MAN), “Operations and Technology Management” (OPS&TECH), and “Operations Research and Management Science” (OR&MANSCI). This last step allowed me to reduce the number of relevant articles to a total of 518 documents, which have been included in the final database.
The earlier stages are summarised more analytically in Table 1.

Table 1
Phases for the construction of the database

Identification	Records identified from **Scopus database** with year range **1999 – 2023** → **68,225** documents found
Filtering	Added filters: • Document Type: «**Article**» → **29,439** documents found • Source Type: «**Journal**» and «**Trade Journal**» → **28,855** documents found • Language: «**English**» → **26,723** documents found • Subject Area: «**Business, Management and Accounting**», «**Economics, Econometrics and Finance**», «**Decision Sciences**» → **2,973** documents found • Filtering for the major journals in the fields of: "**Ethics, CSR and Management**" (**ETHICS-CSR-MAN**); "**Operations and Technology Management**" (**OPS&TECH**); "**Operations Research and Management Science**" (**OR&MANSCI**) → **518** documents found
Included	Studies included in the analysis: **518**

Figure 1
Number of publications per year

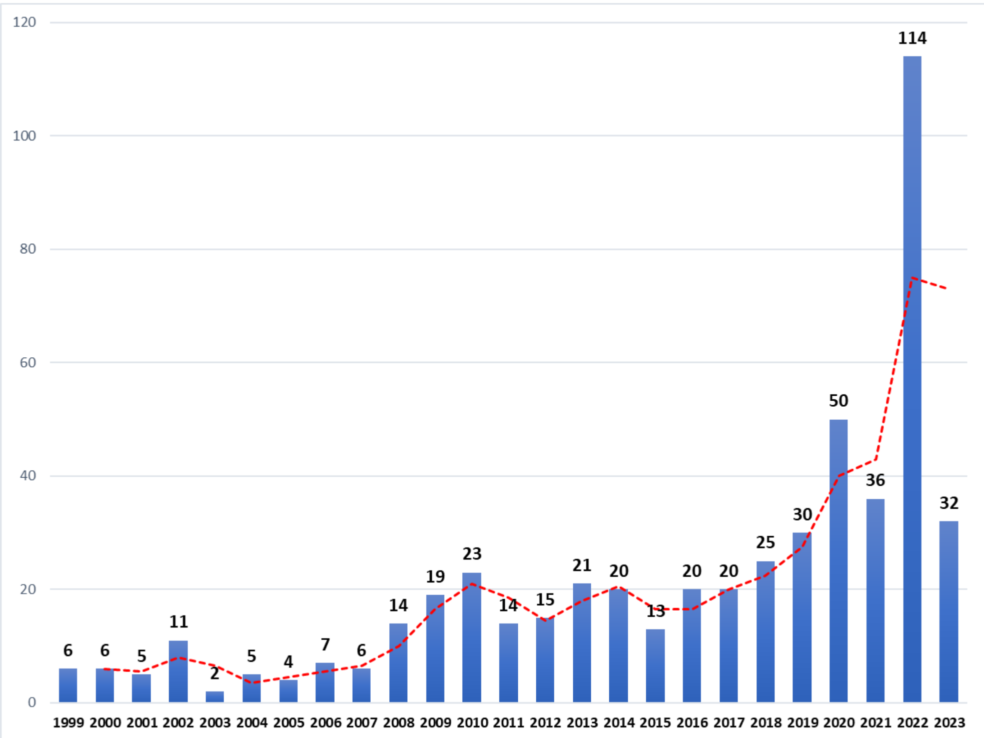


Table 2
Top journals, divided by fields and ranked by the number of citations

Fields	Source Title	Citations
OPS&TECH	International Journal of Production Research	148
	International Journal of Production Economics	69
	Production Planning and Control	36
	International Journal of Supply Chain Management	27
	IEEE Transactions on Engineering Management	22
	International Journal of Operations and Production Management	15
	Production and Operations Management	12
	Manufacturing and Service Operations Management	8
	Journal of Operations Management	5
OR&MANSCI	European Journal of Operational Research	77
	Annals of Operations Research	27
	Computers and Operations Research	24
	Journal of the Operational Research Society	23
	Operations Research	6
	Management Science	5
	Informs Journal on Computing	5
	Journal of Heuristics	5
	International Journal of Applied Decision Sciences	4
	Grand Total	**518**

3.3 PRELIMINARY ANALYSIS

Before explaining the process that has been used for visualizing the database and delving into the actual analysis that is given in the "*Results*" chapter, in this paragraph I will illustrate and highlight some important information about the resulting database to provide a general overview. More specifically, this preliminary analysis will be conducted by describing Figure 1 and Table 2.

Figure 1 depicts the distribution of the 518 publications across the selected year range and allows us to get a first idea about how the topic is treated in the available literature and how it has been attracting growing attention in recent years. Indeed, compared with the early years of the research characterized by a reasonably stable number of articles, the general trend of the flowchart shows a clear and increasing awareness of the potential value of artificial intelligence in supply chain management. This tendency led to a peak of 114 papers published in 2022, making it a pivotal year for both my research and the topic in general.

On the other hand, Table 2 delves deeper into the sources used in this study and offers a summary of how the articles are distributed in relation to the fields and journals to which they belong. After filtering the database according to the steps outlined in the previous paragraph and in Table 1, the relevant papers were found within the domains "Operations and Technology Management" and "Operations Research and Management Science", as well as across eighteen different, major journals.

“OPS&TECH” is the leading field for the included studies, with almost over twice as many publications as the next domain (342 vs. 176 articles). Within this field, the prominent sources are undoubtedly the “*International Journal of Production Research*” and the “*International Journal of Production Economics*”, with a combined total of 217 publications that represent 42% of the whole database. Conversely, in the “OR&MANSCI” domain the “*European Journal of Operational Research*” emerges as the most influential source with a total number of 77 papers. Despite having fewer publications, it has a significant contribution to this research considering that it provides us with a different perspective and approach to the topic.

In general, this preliminary analysis gives us a first overview of the database of articles that will be better analysed and described later in this thesis. The distribution of publications among various fields and journals demonstrates the interdisciplinary nature of the research, which incorporates elements of operations management, computer science, information technology, and decision sciences. These results establish the groundwork for a more thorough investigation of the body of existing literature and offer insightful information for future study and discussion.

3.4 VISUALISATION OF THE DATABASE

For visualising and analysing the resulting database from the previous paragraph, I selected VOSviewer (version 1.6.19), which is a computer program that uses the VOS mapping technique[2] for constructing and viewing bibliometric maps (Eck and Waltman, 2009). On VOSviewer are supported only maps that use the distance-based approach, which differentiates from the graph-based method because it relates the strength in the relation between two items to their distance in the map. Consequently, a smaller distance generally indicates a stronger relationship (Van Eck and Waltman, 2014).

Using the described program, I constructed three different maps based on the co-citation, bibliographic coupling, and co-occurrence analyses, all of which are presented in the Standard Network Visualisation.

Figure 2 shows the first map, which was constructed using the co-citation technique with the cited references as unit of analysis. By choosing a minimum number of five citations, of the total 25,985 cited references the largest set of items consisted of forty-one, which are the ones shown in the map.

[2] Where VOS stands for *visualisation of similarities* (Eck and Waltman, 2009).

Figure 3 displays the following map, created using the bibliographic coupling on the documents of the database. With a selected minimum number of sixty citations of the 518 documents fifty-three items were the largest batch of connected elements.

Finally, Figure 4 shows the third and last map of the bibliometric analysis, constructed with the co-occurrence of the authors' keywords technique. Firstly, I created an appositely made Thesaurus text file to clean the collection of keywords and avoid duplications and repetitions. By doing this, the same, unique concept is still referenced despite variances in the plurals or the synonyms (such as "ai" or "supply chains"). Afterwards, by selecting a minimum number of five occurrences, of the total 1,730 keywords I displayed on the map the fifty-four that met the threshold.

In the next chapter dedicated to the analysis of the results, I will better illustrate the maps just described, and provide enlightenment on what is known and what is not known, basing the systematic review on the most relevant publications regarding the topic.

Figure 2

Co-citation analysis of the cited references (41 items shown)

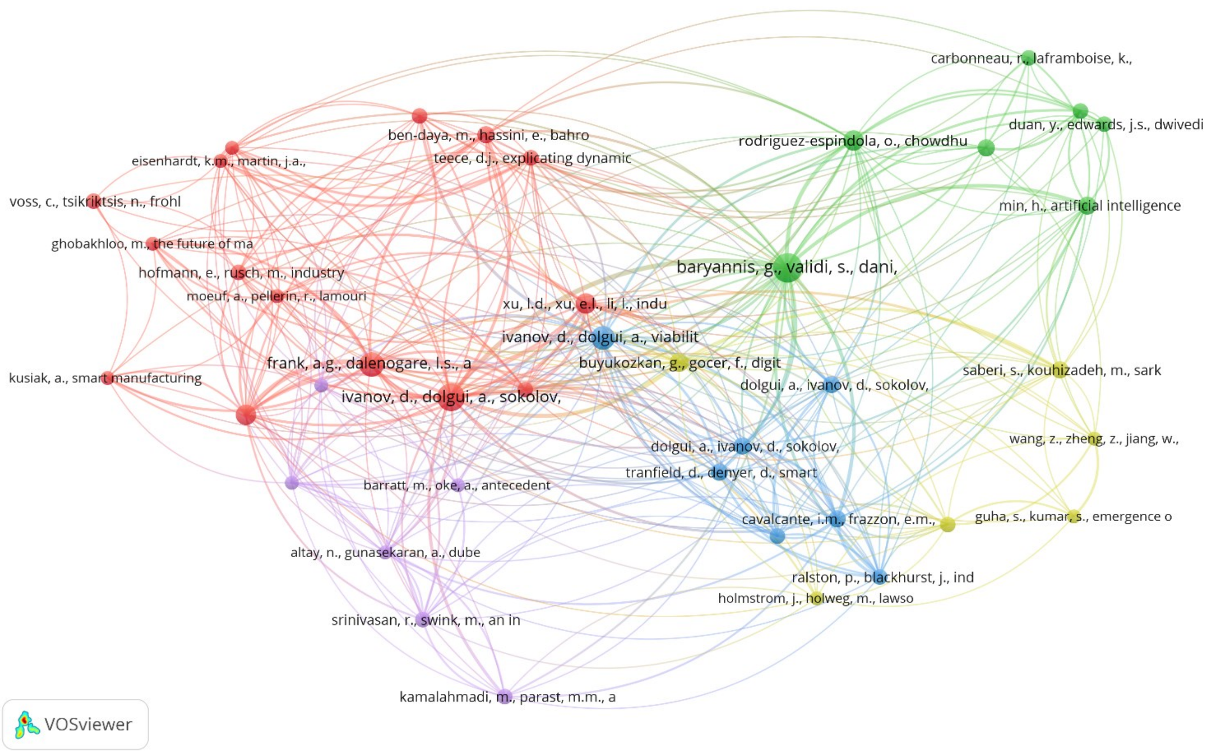


Figure 3
Bibliographic coupling of the documents (53 items shown)

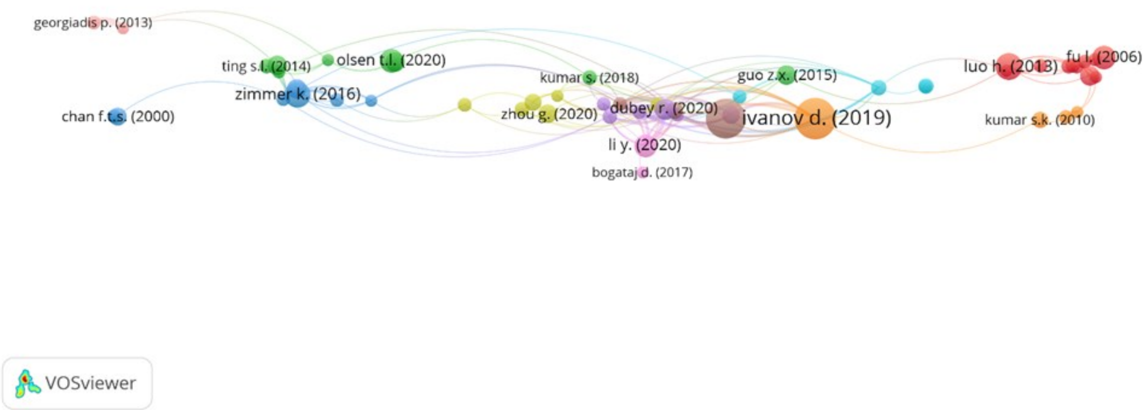
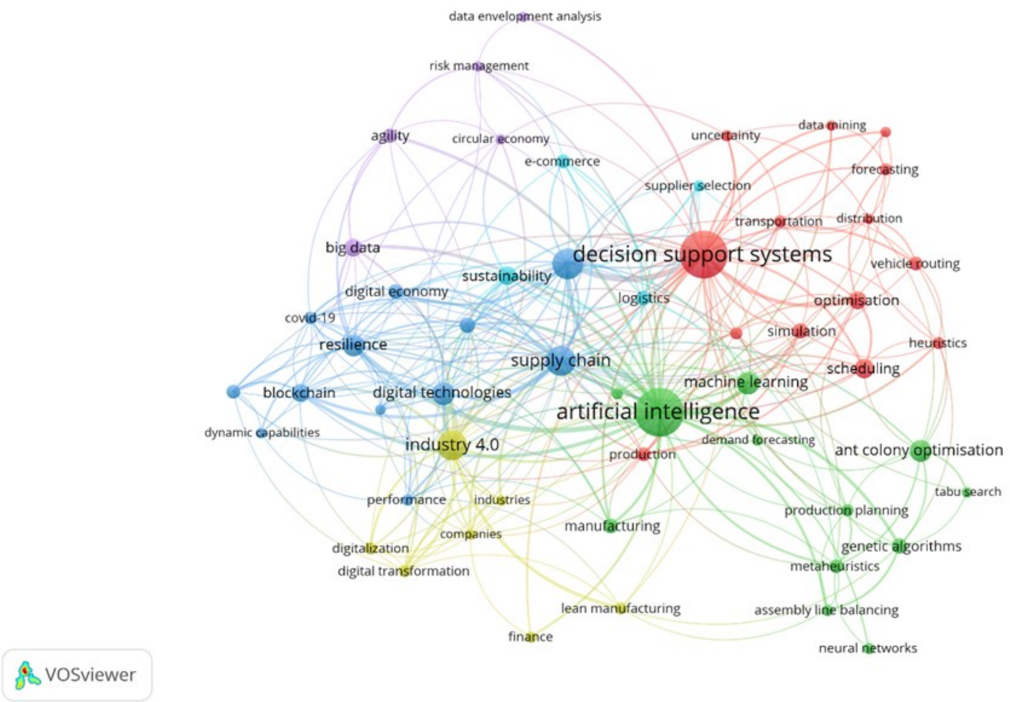


Figure 4
Co-occurrence of the authors' keywords (54 items shown)



4. RESULTS

The present chapter delves into the real and more concrete analysis of what has been so far described and presents the key findings of the research database by providing us with valuable insights and patterns.
This section is divided into three further paragraphs, each of which is dedicated to the description and the study of the maps created using VOSviewer. These maps serve as informative visual representations, illustrating the thematic clusters and influential research articles, by also offering an image of the past, present and future of this important topic in business and scholarly research (Van Raan, 2004).

4.1 FIRST MAP: CO-CITATION OF CITED REFERENCES

As previously outlined in the "*Methodology*" chapter, the initial map was built by using the co-citation of the cited references technique. This type of analysis helps to reveal the historical impact and interconnections among publications, by identifying the significant works that influenced the field. It therefore showcases the fundamental research and influential studies that have paved the way for the current groundwork and advancements in the subject area (Small, 1973). This first map is composed of five clusters, each of which has a distinct number of articles and will be better analysed.
The first cluster (represented in red colour in the map) encompasses a total of fifteen articles. However, for the purposes of this discussion, we will primarily focus on two articles that have garnered significant attention based on their citation counts: Ivanov et al. (2019), with nineteen citations, and Frank et al. (2019), with fifteen citations. This collection of articles predominantly establishes a theoretical groundwork and can be broadly categorized under the theme of "Industry 4.0 Technologies and their influence on Supply Chain Management," therefore including applications that go beyond the narrower field of AI. In more detail, the paper of Ivanov et al., (2019) offers an extensive literature review and a framework analysis for the topic, with particular regard to the risk mitigation and resilience sub-areas. The authors' study is grounded on the logical premise that the interplay between supply chain management and digital technologies has implications for managing disruption risks within the supply chain. By recognizing the connections between smart technology and supply chain disruption risk management, the paper sheds light on the interrelations and highlights the significance of incorporating intelligent technologies to enhance risk management practices, especially for the ripple effect. Inside this context, it is important to outline a definition for this last notion.

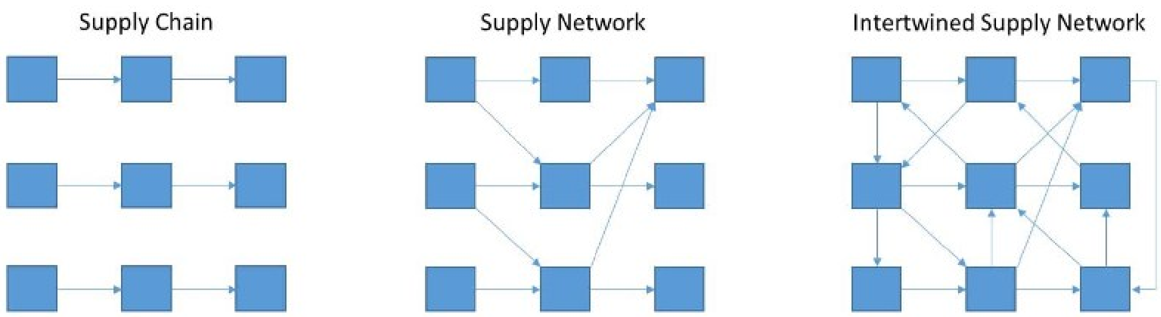
By “ripple effect” we refer to a particular disruptive phenomenon that changes the structure of the supply chain. Unlike the localized impact of the “bull-whip effect”, the ripple effect manifests as a cascading disruption that affects various aspects such as sales, service levels, costs, and more. It extends beyond mere demand and supply imbalances at the operational level, encompassing broader consequences throughout the SC (Ivanov et al., 2019). The authors conclude that multiple, potential applications can be identified to mitigate these risks and improve supply chain’s robustness. As previously discussed, smart technologies are particularly useful in enhancing the visibility, traceability, and prediction within the SC by leveraging track and tracing technologies (Internet of Things – IoT; Blockchain, etc.), AI algorithms, and machine learning models, notably effective for analysing big data.
Following a similar path to the one of the previous authors, Frank et al., (2019) explore the impact of industry 4.0 technologies with specific attention to the manufacturing industry. The originality of their contribution lies in their analysis of the adoption and implementation patterns of these cutting-edge techniques on a sample of 92 manufacturing companies. Indeed, the authors reveal a strong relationship between the level of implementation and the companies’ size, likely attributed to the substantial investments required for such innovations. Study results also highlight that businesses that have advanced in their adoption of Industry 4.0 are embracing all of its technologies rather than focusing on specific ones. This suggests that the increasing maturity on this side involves integrating multiple technological solutions rather than replacing one technology with another. Finally, the authors enrich their contribution by providing a conceptual framework that distinguishes between “front-end” and “base” technologies (Frank et al., 2019, pg. 16). The first ones comprise the four main dimensions of Smart Manufacturing, Smart Products, Smart Supply Chain and Smart Working; while the base technologies are means that serve as a foundation by providing connectivity and intelligence, such as IoT, cloud services and big data.

The second cluster is depicted with dark green colour in the visualization and comprises seven different articles with a more specific (and more relevant to this thesis) focus on the fields of artificial intelligence and supply chain management. The paper that was cited the most (with a total of twenty-one times) in the constructed database is the work of Baryannis et al. (2019). The authors pay particular attention to the risk management topic, recognizing the criticality of adopting a proactive strategy rather than a reactive one in today's highly competitive and volatile business environment. They therefore emphasize the importance of predicting the potential impact of disruptions and minimizing risks and damages that delayed responses could imply.

The researchers' points are nowadays stronger and even more central, considering the very recent Covid-19 pandemic and its repercussions for SCM. Like other authors referenced in the present thesis, Baryannis et al. (2019) remark on the potential effectiveness of AI technologies in addressing these challenges, especially in the processes of risk prediction, identification, assessment, mitigation, and monitoring. Overall, this article presents valuable insights on the topic and provides clear guidelines for future research.

The third cluster (blue colour) in my opinion can be located halfway between the first and second presented groups of articles. Indeed, its seven publications can be grouped under the general label of "SC resilience and artificial intelligence", encompassing topics such as supply chain survivability, ripple effect and evidence-informed management. Among these studies, the work of Ivanov and Dolgui (2020) stands out with fourteen citations in the database. The paper analyses the viability of intertwined supply networks (ISNs) in the context of the Covid-19 outbreak. With ISN we refer to a comprehensive network comprising interconnected supply chains that collectively ensure the continuous provision of goods and services to society and markets (see Figure 5). While this interconnectedness facilitates the smooth movement of products and services within the network, it also exposes the structure to greater dynamism and vulnerability to potential impacts. For these reasons, the authors emphasize that, in SCM, survivability and viability should involve the ability to adapt, transform, and withstand shocks and persistent uncertainties, rather than solely focusing on recovery from disruptions.
The outlining of these concepts and the delineation of this supply chain design are the factors that make this study influential for my research.

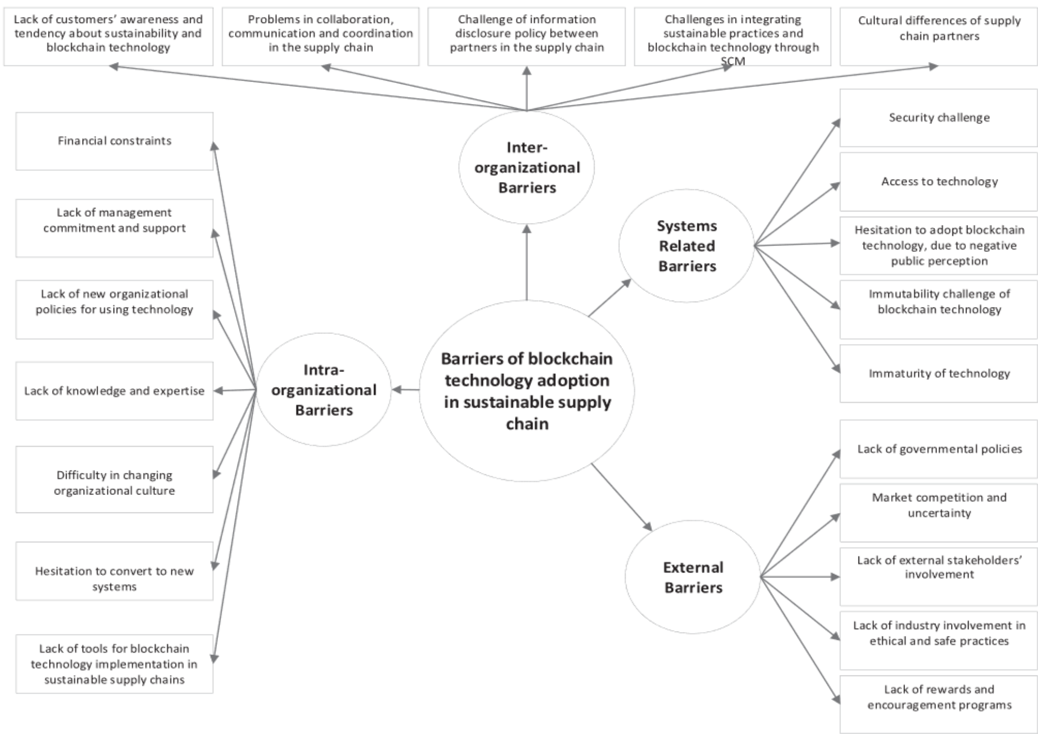
Figure 5
Linear supply chains, supply networks and intertwined supply networks, from Ivanov and Dolgui (2020)



The fourth cluster is represented in light green and it consists of six different articles that predominantly revolve around the topic of "Digitalization and its Impact on SCM". The novelty and originality of these papers stand in their analysis of more specific and effective tools, in particular the blockchain technology.

Indeed, Saberi et al. (2019) focus their research on the study of this digital ledger technology and its applications for improving the traceability and sustainability of the SC. Starting with the basics, we define blockchains as "[…] *tamper evident and tamper resistant digital ledgers implemented in a distributed fashion (i.e., without a central repository) and usually without a central authority (i.e., a bank, company, or government). At their basic level, they enable a community of users to record transactions in a shared ledger within that community* […]" (Yaga et al., 2018, pg. 12). This technology gained its popularity in 2008 with the creation and introduction of the Bitcoin cryptocurrency, and it is attracting growing attention thanks to its operating in a decentralised network which, along with the smart contractual relationships, guarantee a secure and traceable flow of value and information. With "smart contract" we refer to a self-executing contract that presents the terms of the agreement written into lines of code and executes them between the parties without the need of intermediaries or manual intervention. Despite the multiple presented benefits, the authors highlight the existing barriers for the application of the blockchain technology: financial constraints, communication and coordination issues, lack of government policies and uncertainty, challenges regarding the security and immutability of the technology just to mention a few (see Figure 6) The authors therefore emphasise the need for transdisciplinary researchers to pragmatically analyse the practical implications and potential complications associated with harnessing the capabilities of blockchain technology.

Figure 6
Barriers of blockchain technology adoption in sustainable supply chain, from Saberi et al. (2019)



The fifth and final cluster is represented with purple colour on the map and it includes six publications that are all centred on the sub-fields of SCM that treat supply chain agility and flexibility. The most cited article was the work of Srinivasan and Swink (2018), which examines the relationship between visibility, flexibility, and supply chain analytics from the viewpoint of Organizational Information Processing Theory (OIPT). This last notion refers to a theoretical framework that focuses on how organizations gather, interpret, and use information to make decisions under the assumption that organizations' effectiveness is determined by how well they handle these processes (Galbraith, 1973; Huber, 1991). The authors' main and most relevant finding from their study is that the integration of organizational flexibility and analytics capability has a stronger positive correlation with operational performance compared to either capability alone. In essence, the researchers underline that analytics capability offers valuable insights into aligning supply and demand, while organizational flexibility empowers firms to determine the most effective methods for implementing the necessary changes.

4.2 SECOND MAP: BIBLIOGRAPHIC COUPLING

The second map was generated through the application of the bibliographic coupling technique, where the linkages represent connections between articles that have a shared reference or citations to a common document. The map is composed of ten clusters, with variable number of articles that cover a time span of approximately twenty years. This analysis therefore provides us with a temporally cross-sectional perspective on the field and allows us to gain insights into the progress of scholarly research and identify specific sub-areas that require further exploration in future studies.

The first cluster of the map (depicted with red colour) encompasses a total of eleven, more analytical publications, broadly centred on the topics of optimisation and problem-solving techniques applied in various industrial and logistical settings. Most of the included papers treat the topic of Ant Colony Optimisation (ACO) which is a concept inspired by the behaviour of some ants' species. Just like ants deposit pheromone trails on the ground to indicate favourable paths that should be followed by other colony members, in these algorithms "[…] *a number of artificial ants build solutions to an optimization problem and exchange information on their quality via a communication scheme* […]" (Dorigo et al., 2006, pg. 30). Within this batch of articles the most cited publication is the work of Luo et al. (2013) whose novelty stands in the proposal of a new, meta-heuristic approach called Multi-Objective Ant Colony Optimisation (MOACO), which analyses production efficiency also in light of electric power cost (EPC) and time-of-use (TOU) electricity prices.

By using the hybrid flow scheduling (HFS), where a group of production stages has to be processed and arranged, the authors conclude that the MOACO outperforms the other multi-objective algorithms even if with a slower resolution.

The second cluster (highlighted in dark green) and the sixth cluster (represented by light blue) consist of eight and four publications, respectively. They both share a common focus on integrating emerging technologies in supply chain management in order to enhance performance measures such as efficiency, sustainability, and responsiveness. These studies contribute to the literature by providing comprehensive analyses and overviews of various technologies and tools that have received limited attention thus far. The topics covered encompass RFID technology, the data mining process, 3D printing, and the previously mentioned blockchain, AI, and Internet of Things (IoT). Notably, the most highly cited article in this cluster is the study conducted by Olsen and Tomlin (2019) which analyses the different Industry 4.0 technologies applied to operations management. The authors begin their study by remarking that, even though the notion of "Industry 4.0" can be seen as a simple set of diverse technologies, its value lies in the potential synergies among them. For instance, additive manufacturing (AM), also known as 3D printing, is a process that involves creating three-dimensional objects by adding material layer by layer. This has multiple implications for traditional business operations, especially for new product design, as it allows for significant time and cost savings in prototyping. Similar reasoning can be conducted for the Internet of Things. In particular, the authors focus on the RFID (Radio Frequency Identification) technology which improves the tracking of physical objects by providing them with a unique identifier that can be read remotely, making it an accurate tool for inventory management. Despite not being a very recent publication in the analysed field, this article stands out for its comprehensive description of these technologies and their associated opportunities and challenges.

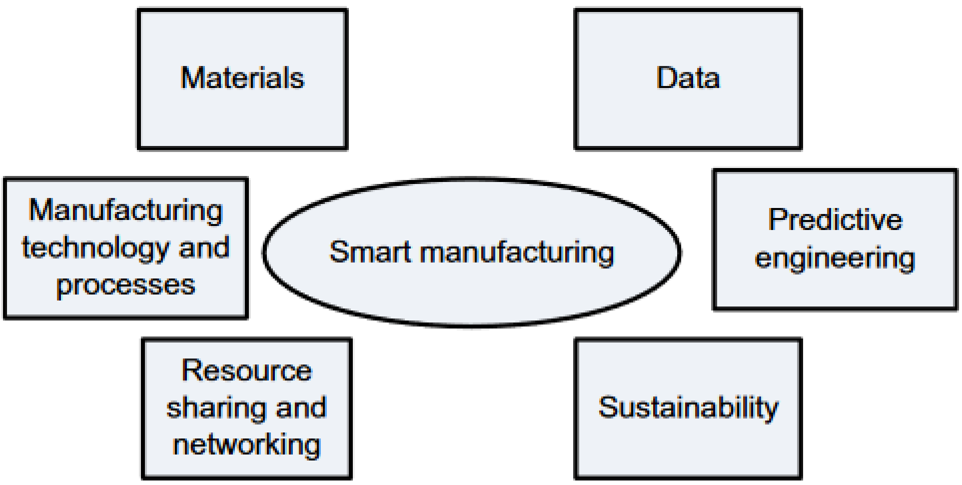
The third and fourth clusters, distinguished by dark blue and light green colours on the map, consist of a combined total of thirteen publications (seven and six, respectively). In general, the two clusters concentrate on themes related to digital transformation, human-robot collaboration, and the utilization of intelligent decision-support tools with the general objective of optimising operations and supply chain management. Despite being only the third, most cited paper in the collection, the work of Zhou et al. (2020) offers more original and diverse perspectives by exploring the implementation of knowledge-based approaches for improving manufacturing processes and decision-making. The authors present a novel framework aimed at establishing a knowledge-driven twin manufacturing cell (KDTMC), which draws inspiration from cellular manufacturing principles to create more cost-efficient and flexible production processes. Within this context, a virtual and autonomous “twin” cell is created and is equipped with the capacities of self-thinking, self decision-making, and self-improving thanks to the integration of real-time data and predictive models. By incorporating various sources of knowledge, the intelligent manufacturing cell enhances its ability to understand, simulate, and analyse various scenarios, detect anomalies, and make informed decisions. The authors conclude their article by highlighting the feasibility and effectiveness of the proposed KDTMC while acknowledging the limitations of their study, from the data security issue to the necessity for interdisciplinary collaboration to apply these concepts to everyday reality.

The fifth cluster can be identified with the purple colour on the map, and it comprises six publications. These predominantly fall within the scope of "Big Data Analytics and AI-Driven Innovation in Operations Management". They delve into how collaboration and information alignment can improve SC’s responsiveness and agility. The article that received the most citations is the work of Dubey et al. (2020), which explores the aforementioned topics especially from the angles of entrepreneurial orientation and dynamic environmental conditions. The authors begin by highlighting the centricity of data as a valuable asset for contemporary organizations, especially considering the digitalization process and the increasing volume of data generated. By analysing the information collected through a survey from a sample of 256 manufacturing firms, the authors conclude that organisations with more proactive and innovative orientation are more likely to invest in these technologies and exploit their potentiality. Indeed, the entrepreneurial traits of proactiveness, risk-taking, and innovativeness are essential to harness the power of BDA-AI, particularly in more dynamic environments where is important to forecast and sense the impellent changes in the market. This publication provides us with a significant contribution considering that it sheds light on the fact that these very powerful and efficient technologies can lead to no improvements in operational performance if they are not accompanied by the right orientation and capabilities.

The seventh cluster is denoted by the colour orange on the map, and it consists of four articles. Among them, the most highly cited paper is the study conducted by Ivanov et al. (2019), which has garnered an impressive number of 708 citations, making it the most cited paper in the entire database. As this paper has already been discussed in the previous paragraph dedicated to the analysis of co-cited references, I will provide a brief overview of the general topics covered in this cluster and encourage you to refer to the respective chapter for a more detailed analysis. The articles broadly revolve around various aspects of SCM, from workload balancing to cost minimisation with embedded risk and the impact of computational intelligence and digital technologies. Spanning almost two decades, these four publications have made significant contributions to the advancement of supply chain management by effectively focusing on the aforementioned critical challenges.

Getting to the end, the eighth cluster can be identified with the brown colour on the map and its three publications can be broadly gathered under the topics of “Lean Manufacturing and Digitalisation”, also encompassing their combined impact on improving operational performance. The work of Kusiak (2018) ranks as the second most cited publication in the database (with 654 citations), representing another important contribution to the topics of AI and SCM. The author defines smart manufacturing as “[…] *an emerging form of production integrating manufacturing assets of today and tomorrow with sensors, computing platforms, communication technology, control, simulation, data intensive modelling and predictive engineering* […]” (Kusiak, 2018, pg. 1), making this concept an evident trademark of the ongoing industrial revolution. Additionally, Kusiak identifies six central concepts for smart manufacturing, acknowledging that they are dynamic and interconnected rather than exhaustive or static (see Figure 7). These are materials, manufacturing technology and processes, resource sharing and networking, data, predictive engineering, and sustainability, which in their advancements and interconnections provide companies with more effective tools and a new vision on the viability of manufacturing processes. Finally, the author further reinforces these pillars by proposing ten conjectures that shed light on the opportunities and challenges surrounding the acceptance of these transformative changes in manufacturing. These suppositions outline the characteristics of future smart manufacturing and its potential developments (digitalisation, reliance on data collection, predictive modelling and optimisation, etc.), paving the way for future research and analysis.

Figure 7
Six Pillars of Smart Manufacturing, from Kusiak (2018)



The last two clusters are depicted with pink and fuchsia colours and they jointly comprise four publications. Although the two batches of articles focus on different, more specific topics, a common thread can be found in their analysis of the role of digital technologies and their impact on supply chain management, economic performance, and environmental sustainability. A bridge between the four papers can be identified in the work of Li et al. (2020), which received the most attention with its 219 citations. Similar to the aforementioned article of Srinivasan and Swink (2018), this empirical study employs the perspective of Information Processing Theory (IPT) to examine how smart technologies influence economic and environmental performance in the context of Industry 4.0. The originality of the authors' contribution stands in their proposal of a moderated mediation model, which is a statistical framework where the relationship between an independent variable (X) and a dependent variable (Y) is influenced by the presence of a third variable called the mediator (M) and a fourth variable called the moderator (W). In essence, this means that the strength or direction of the mediation may vary depending on the levels or values of the moderator variable. (Preacher et al., 2007). In their research, Li et al. identify digital supply chain platforms as mediators, indicating that these platforms help to better explain the impact of digital technologies on economic and environmental performance, with environmental dynamism moderating the indirect effect. This leads to the conclusion that smart technologies and supply chain platforms play a more crucial role in a dynamic environment.

4.3 THIRD MAP: CO-OCCURRENCE OF AUTHORS' KEYWORDS

The third and final map is constructed using the technique of the co-occurrence of the authors' keywords, which provides useful insights into the literature's structure and dynamics, aiding researchers in discerning key trends, influential authors, and important research themes. The map is composed of six clusters, each housing a distinct number of keywords (see Table 3). While the depth of analysis for individual clusters might not be as extensive as in prior maps, where selected articles were closely examined, it remains feasible to recognise primary thematic domains. By considering the prevalence of specific keywords within these domains, we can identify prospective trajectories for future research endeavours which encompass emerging technologies, sustainability, and strategies for navigating uncertainties in SCs.

Table 3
Clusters of the third map (co-occurrence of authors' keywords)

CLUSTER 1	CLUSTER 2	CLUSTER 3	CLUSTER 4	CLUSTER 5	CLUSTER 6
Decision Support Systems 96 occurrences; 88 link strength	*Artificial Intelligence* 101 occurrences; 128 link strength	*Supply Chain Management* 40 occurrences; 62 link strength	*Industry 4.0* 38 occurrences; 55 link strength	*Big Data* 14 occurrences; 19 link strength	*Sustainability* 15 occurrences; 31 link strength
Scheduling 16 occurrences; 16 link strength	*Machine Learning* 22 occurrences; 21 link strength	*Supply Chain* 38 occurrences; 77 link strength	*Digital Transformation* 7 occurrences; 18 link strength	*Agility* 9 occurrences; 15 link strength	*Logistics* 9 occurrences; 15 link strength
Optimisation 14 occurrences; 22 link strength	*Ant Colony Optimisation* 21 occurrences; 14 link strength	*Digital Technologies* 23 occurrences; 36 link strength	*Digitalization* 7 occurrences; 10 link strength	*Circular Economy* 5 occurrences; 11 link strength	*E-commerce* 8 occurrences; 11 link strength
Simulation 11 occurrences; 17 link strength	*Genetic Algorithms* 11 occurrences; 16 link strength	*Resilience* 21 occurrences; 46 link strength	*Lean Manufacturing* 7 occurrences; 11 link strength	*Data Envelopment Analysis* 5 occurrences; 4 link strength	*Supplier Selection* 6 occurrences; 10 link strength
Production 8 occurrences; 19 link strength	*Manufacturing* 9 occurrences; 14 link strength	*Blockchain* 14 occurrences; 30 link strength	*Finance* 6 occurrences; 6 link strength	*Risk Management* 5 occurrences; 10 link strength	
Vehicle Routing 8 occurrences; 10 link strength	*Metaheuristics* 8 occurrences; 14 link strength	*Operations Management* 10 occurrences; 15 link strength	*Companies* 5 occurrences; 18 link strength		
Dynamic Programming 7 occurrences; 10 link strength	*Production Planning* 7 occurrences; 11 link strength	*Digital Economy* 9 occurrences; 17 link strength	*Industries* 5 occurrences; 15 link strength		
Forecasting 7 occurrences; 8 link strength	*Assembly Line Balancing* 6 occurrences; 10 link strength	*Additive Manufacturing* 8 occurrences; 15 link strength			
Heuristics 7 occurrences; 10 link strength	*Data Analytics* 6 occurrences; 9 link strength	*Covid-19* 7 occurrences; 21 link strength			
Transportation 7 occurrences; 11 link strength	*Neural Networks* 6 occurrences; 3 link strength	*Performance* 6 occurrences; 14 link strength			
Uncertainty 6 occurrences; 9 link strength	*Demand Forecasting* 5 occurrences; 7 link strength	*Dynamic Capabilities* 5 occurrences; 8 link strength			
Data Mining 5 occurrences; 8 link strength	*Tabu Search* 5 occurrences; 4 link strength	*Information Systems* 5 occurrences; 13 link strength			
Distribution 5 occurrences; 9 link strength					
System Dynamics 5 occurrences; 7 link strength					

The first cluster is depicted with red colour and it is the one containing the most keywords, with a total of fourteen items. This collection converges upon the overarching theme of "Operational Optimisation and its attendant Methodologies", as underscored through keywords like *Forecasting*, *Optimisation*, *Production*, *Scheduling*, and *Transportation*. A notable pattern emerges with keywords like *Data Mining*, *Dynamic Programming*, and *Simulation*, reflecting a growing inclination toward data-driven methodologies and advanced analytics to address intricate supply chain challenges. The prominent term in the cluster is the keyword *Decision Support Systems*, which occurs ninety-six times. This extensive coverage, coupled with its interconnectedness to terms spanning all clusters, reaffirms its central role as a critical tool for enhancing operational performance. With the exception of this last notion, the remaining keywords have a relatively lower frequency, probably suggesting a well-established foundation, even if with room for refinement.

The second cluster, distinguished by a dark green colour, encompasses a collection of twelve keywords that can be traced to two main subgroups. The first one relates to the area of computational intelligence, prominently evident in keywords such as *Artificial Intelligence*, *Data Analytics*, *Machine Learning*, and *Ant Colony Optimization*. These draw considerable attention due to their frequency and robust linkages with other clusters. In particular, the prevalence of terms like "artificial intelligence" and "machine learning" echoes the growing trend of harnessing data-driven insights and predictive analytics to make informed decisions across various stages of the supply chain.

On the other hand, the second subgroup is characterized by keywords like *Manufacturing*, *Demand Forecasting*, *Production Planning*, etc. Clearly, the focus is on the complementary side of the manufacturing practices that can gain an advantage from the adoption of the computational intelligence techniques just mentioned, strengthening the importance of integrating such technologies in modern companies.

The next collection of twelve keywords can be identified in dark blue colour and it has its preeminent spotlight on the complex interplay between "Supply Chain Management Dynamics and Digital Transformation". Just as in the preceding cluster, a similar dichotomy of keyword groups comes into view. One is centred on the recent technological upheavals (as the terms *Additive Manufacturing*, *Blockchain*, *Digital Technologies* make us understand); while the other (exemplified in words such as *Supply Chain*, *Operations Management*, *Dynamic Capabilities*) accentuates the dynamic nature inherent to modern supply chains and establishes a strong nexus among these critical elements. An interesting insight can be derived from the appearance of the keywords *Resilience* and *Covid-19*, with the latter representing the major disruption in the last decade. This underscores the significance of exploring supply chain agility and risk management in the context of unforeseen disruptions, thereby amplifying the criticality of these dimensions.

The fourth cluster is depicted in light green on the map, and it comprises seven keywords. These delve into the field of Industry 4.0, in particular investigating how emerging technologies are reshaping industries and organisational dynamics. Evidently, the pivotal keyword *Industry 4.0* stands out both in frequency and its interconnections with the other clusters, underscoring its centrality and relevance in the modern industrial landscape. The inclusion of terms such as *Companies*, *Digitalization* and *Finance* seems to suggest a comprehensive exploration of how businesses adapt to the digital era and how they leverage these new technologies to enhance their operational efficiency and viability. Another interesting connection can be traced to the keyword *Lean Manufacturing*, which could indicate an examination of how lean principles integrate with the latest advancements. Nevertheless, this collection of keywords presents relatively fewer occurrences compared to the other clusters (even if with quite strong linkages), potentially suggesting a more mature research foundation in this domain.

Approaching the conclusion of this analysis, the fifth cluster can be identified with the purple colour and it encompasses a total of five keywords. Collectively this collection offers insights into the "Strategies for Smart Decision-Making", in order to improve operational efficiency.

The two terms *Agility* and *Risk Management* are closely related to the concepts already seen in the third cluster and they again stress the importance for organisations to be flexible and agile in nowadays rapidly changing and dynamic environments. The preeminent keyword in the cluster is notably *Big Data*, remarking its centrality for modern decision-makers and emergent intelligent tools. This is especially relevant considering the great volume of data generated and the precious information and insights that can be taken from analysing large and complex datasets. One last compelling observation retrievable from this cluster comes from the term *Data Envelopment Analysis*, a concept not previously encountered in this research. This refers to a quantitative technique used to measure the efficiency of decision-making units by comparing their inputs and outputs (Cooper et al., 2011), making it a significant tool for evaluating and optimising companies' performance.

The sixth and final cluster is depicted with a light blue colour and it comprises only four keywords. Given the limited number of terms in this collection, identifying a singular theme is more challenging. However, taking a broader perspective, we can say that the focal points relate to the fields of *Logistics* and *Sustainability*. The latter is particularly frequent and presents multiple linkages with the other collections, probably indicating a growing emphasis on environmentally conscious practices. Indeed, in contemporary business landscapes, companies are compelled to demonstrate efficiency not only in resource utilization and economic aspects but also in their impact on the environment and society. Additionally, for its connections with concepts from other clusters such as *Artificial Intelligence*, *Supply Chain*, *Digital Technologies*, and *Risk Management*, the keyword *E-commerce* seems to provide interesting insights. This indicates a focus on exploring how these digital pathways transform traditional business models and reconsider customer interactions, driving the need for innovative strategies. Future studies within this cluster could therefore delve into new approaches that integrate sustainable principles with the logistics of e-commerce.

5. CONCLUSIONS

This chapter culminates an exploration into the intricate and highly relevant intersection of artificial intelligence and supply chain management, employing bibliometric analysis and the VOSviewer software as primary analytical tools. As consistently emphasized throughout this study, in nowadays increasingly competitive business environment it is crucial to properly analyse the advantages and disadvantages derived from the potential adoption of these new tools in order to enhance operational efficiency within companies. Indeed, it remains indisputable that AI and smart technologies employ disruptive power that is reshaping not only the economic sphere but also various domains such as healthcare, agriculture, and transportation. Another significant and recurring theme is the one of resilience and risk management, which has gained growing centrality due to the very recent Covid-19 pandemic. This underscores once again the potential gains that can be harnessed from adopting these cutting-edge technologies, including enhancing adaptability and responsiveness.

Thanks to the analysis of the maps created using VOSviewer and the multiple references examined, this research offers an updated and systemic literature review that can serve as a theoretical, cross-sectional knowledge foundation. The usage of a larger database of publications permitted a broader and more general analysis, without having to focus on more specific topics or scenarios. Consequently, the "*Results*" section has unveiled numerous insights, shedding light on the current state of the art and underscoring the limited research and publications in the more specific field of artificial intelligence and supply chain management. Indeed, as we go over the analysis of the maps generated through co-citation and bibliographic coupling techniques, associated with the assigned labels, it becomes evident that the majority of foundational theoretical groundwork pertains to relatively older works. These works possess a broader emphasis on digital technologies and the ongoing Industry 4.0 transformation. This further solidifies the principal aim of my thesis, which is to furnish an updated literature review with a particular emphasis on the intersection between AI and SCM, addressing the dearth of research in this specific area.

Despite the novelty and originality of the methodology and the general contribution, this thesis presents some limitations and avenues for further exploration. Indeed, it is evident that the research primarily offers theoretical insights, that necessitate a more concrete discussion of the practical applications and implications of such technologies. An interdisciplinary collaboration could delve into the feasibility and applicability of these technologies in specific scenarios, thereby furnishing decision-makers with more pragmatic insights.

Furthermore, it would be important to delve more extensively into the negative counterparts and the potential problems deriving from these technologies. Many authors have devoted attention to this other side of the coin, remarking that no evolution or transformation occurs without the associated cost. One example is the one regarding the Human-AI symbiosis and the implications related to its potential collaboration. It is quite evident that in many sectors and many functions these new technologies and intelligent robots will and are already replacing humans, warranting careful consideration. However, a crucial distinction lies in recognizing that AI usage consists of two distinct phases. While *automation* involves the replacement of humans by AI systems, *augmentation* is the crucial phase wherein these technologies support human decision-making and task execution rather than fully replacing them. It is acknowledged that despite their computational power, these technologies cannot emulate human skills and intuition, qualities that elevate humans to a position of control over such systems (Jarrahi, 2018; Kar and Kushwaha, 2021).

To conclude, this study contributes a systemic perspective on the convergence of artificial intelligence and supply chain management. It underscores the importance of these powerful tools for modern businesses, explores how organisations can leverage them and raises awareness about potential challenges. A comprehensive understanding of the intricate interplay between these domains is indeed indispensable for informed decision-making and strategic planning, guiding businesses into an era of innovation and sustainability.

Total word count (except for Frontispiece, Table of Contents, References, and Acknowledgements): 9065 words

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