Role of Innovative Technologies in Supply Chain Management: Analysis based on BERTopic and Bipartite Graph Models

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Abstract

The supply chain represents a complex network managing the flow of goods, services, and information. Revolutionary technologies including Internet of Things (IoT), blockchain, and artificial intelligence (AI) are fundamentally reshaping supply chain segments, accelerating digital transformation while enhancing operational efficiency. This study examines above 70 thousand publications, indexed in the SCOPUS database**,** related to SCM (analyzing titles, abstracts, and keywords) from 2010 to March 2025, employing BERTopic modeling and bipartite graph analysis to identify emerging patterns. The research uncovers eleven distinct innovation technologies and systematically maps their relationships with various supply chain management (SCM) domains. The results highlight that innovations in SCM are not isolated but broadly integrated across domains, suggesting the importance of cross-departmental collaboration to maximize system-wide benefits. These findings offer strategic insights for practitioners and establish analytical framework for scholars investigating the dynamic intersection of technological innovation and modern supply chain management.

Keywords: supply chain management, innovation, BERTopic, bipartite graph models, SCOPUS.

1. Introduction

Supply Chain Management (SCM) is an indispensable discipline in modern business organizations, facilitating the efficient and transparent flow of materials, information, and financial resources across various stages of the supply chain. Traditional SCM was primarily focused on optimizing logistical business processes, reducing costs, and enhancing operational efficiency. However, contemporary supply chains are becoming increasingly complex due to rising demand, fluctuating market conditions, geopolitical challenges, and the growing need for transparency and sustainability [19]. In this context, adequate changes are necessary to meet these emerging requirements. Technologies, including those associated with Industry 4.0, offer numerous opportunities for positive transformations in SCM.

Innovative technologies such as the Internet of Things (IoT), Blockchain Technology, Artificial Intelligence (AI) and Machine Learning (ML), Autonomous Vehicles and Drones, Digital Twins, Robotic Process Automation (RPA), Big Data Analytics (BDA), Cloud Computing (CC), 3D Printing, Sustainability Initiatives, and Wearable Technology possess the potential to transform traditional SCM into a digital SCM. This transformation is characterized by the automation and optimization of business processes, increased agility, adaptability, precision, and resilience to disruptions. Through their synergy, these technologies not only enhance but also redefine the way supply chains are managed by ensuring more intelligent, highly automated, and interconnected systems [53].

Given the evident positive impact of innovative technologies on SCM, the primary objective of this study is to examine and determine the role of innovative technologies on key SCM areas. To achieve this objective, the following research questions have been formulated:

- RQ1: What is the nature of the relationship between innovative technologies and SCM areas?
- RQ2: Which are the most important types of technology innovations implemented in SCM?

To address these research questions, two analytical approaches were applied: BERTopic modeling and bipartite graph modeling, utilizing a dataset of abstracts from scientific papers indexed in the SCOPUS database from 2010 to March 2025.

The structure of this paper is as follows. Following the introduction, Section 2 presents an overview of SCM domains and innovative technologies. Section 3 provides the research background, while Section 4 outlines the research methodology. Section 5 is dedicated to research findings, whereas Section 6 discusses the research results, conclusions, future research directions, and study limitations.

2. Areas of supply chain management and innovative technologies

The essence of supply chain management, which involves integrating business processes from initial suppliers to end users to provide added value to customers and other stakeholders, emphasizes the need to co-create value in search of sources of competitive advantage for the entire supply chain [29] [52].

Analyzing the structure of the supply chain, it is possible to distinguish 7 areas that are consistent with the phase approach to logistics and are subject to innovation activities [24], [49]: Purchasing, Production, Inventory management, Demand planning, Warehousing, Transportation and Customer service.

In the dynamic world of logistics and distribution, supply chain innovations play a key role in increasing efficiency, reducing costs, and improving the overall quality of services. Innovative technologies can be defined as digital tools or systems that have recently emerged or significantly evolved and that provide new capabilities, enhance performance, or fundamentally transform existing supply chain operations. To determine whether a technology qualifies as innovative in the context of this study, the authors applied criteria based on recent literature: (i) the technology demonstrates transformative potential to reshape supply chain operations, and (ii) it is widely recognized in contemporary academic sources as a key driver of digital transformation. [29, 30], [33] According to Nowicka [30], there are 11 important innovative technologies related to the functional areas of the supply chain presented above, which currently dominate the supply chain management process:
1. Internet of Things (IoT) - allows for real-time tracking of goods and assets, optimizes logistics and reduces delays, enables better inventory management, and reduces losses. [50]

2. Blockchain technology (BT) - providing transparency and security, blockchain provides an immutable ledger for recording transactions and tracking assets. Blockchain ensures traceability of products throughout the supply chain, reducing fraud and improving data security.[23] 3. Artificial Intelligence (AI) and Machine Learning (ML) - AI and ML algorithms optimize routing, demand forecasting, and inventory management. These technologies predict trends and automate decision-making processes. AI is changing the way companies plan and execute supply chain processes[11]. 4. Autonomous vehicles and drones - self-driving trucks and drones have the potential to revolutionize delivery systems by offering faster, more reliable transportation while reducing the need for human intervention. 5. Digital twins - by creating a virtual replica of the supply chain, digital twins allow companies to simulate scenarios, identify inefficiencies, and test solutions without disrupting real-world operations. 6. Robotic process automation (RPA) - automates routine and repetitive tasks, freeing up human resources for more complex activities and improving the accuracy of processes such as order processing and data entry. 7. Big data analytics - analyzing big data helps companies understand customer behavior, predict demand, and optimize inventory levels. 8. Cloud computing - cloud-based platforms facilitate collaboration and information sharing across the supply chain. They offer scalable solutions that can be adapted to varying levels of demand and easily integrated with other technologies. 9. 3D Printing - 3D printing, also known as additive manufacturing, allows for on-demand manufacturing, reducing inventory levels and lead times. It is particularly useful for producing custom parts and prototypes. 10. Sustainability Initiatives - innovations aimed at making supply chains more sustainable include green packaging, energy-efficient shipping options, and waste reduction strategies. These initiatives not only help the environment but also appeal to eco-conscious consumers. 11. Wearable Technology - wearable devices such as smart glasses and wristbands improve worker safety and productivity by providing hands-free access to information and real-time communication capabilities.

3. Literature survey

According to Shahzadi, Jia, Chen, and John [46], the potential of AI lies in enhancing SCM practices, such as resilience, process improvement, and sustainable operations, thereby contributing to better decision-making, increased efficiency, and the adoption of sustainable practices. Furthermore, it is necessary to examine how AI can impact supply chain collaboration, particularly in fostering trust and improving forecasting accuracy to mitigate the bullwhip effect [22]. Patalas-Maliszewska, Szmołda, and Łosyk [34] identified key benefits of integrating AI tools into manufacturing, including predictive maintenance, production planning, and customer relationship management. AI has become a top priority for SCM executives; however, overly optimistic expectations about its impact on SCM performance persist. It is essential to emphasize that technology should not be regarded as an ultimate objective and is rarely sufficient alone organizational and inter-organizational factors play a crucial role in determining outcomes [34].

Due to its characteristics, BT has found applications in SCM, enabling companies to trace the history of products from their origin to their destination. The ability to track and record data throughout the supply chain allows all stakeholders access to high-quality information about specific operations or products [42]. This is particularly beneficial in the food manufacturing industry, as it facilitates secure, transparent, and decentralized information sharing among producers, farmers, and markets. Padma and Ramaiah [32] propose a BT-based solution that employs smart contracts and cryptographic mechanisms to ensure secure and transparent tracking of pharmaceutical products throughout the entire supply chain lifecycle. However, despite the apparent benefits of BT, further research is required to address certain limitations, such as the absence of clearly defined implementation frameworks and insufficient empirical validation of theoretical advantages [3], [39].

IoT provides accurate data and real-time information sharing, which can optimize resource allocation and operational processes within the supply chain, reduce costs, and enhance efficiency and productivity [54]. The integration of blockchain and IoT holds substantial potential for improving transparency and efficiency in logistics, laying the foundation for future advancements in data security and tracking. Unlike traditional solutions, BT and IoT facilitate real-time, secure, and transparent data sharing across various supply chain nodes—from producers to end consumers [44]. The utilization of IoT, wireless sensor networks (WSN), radio-frequency identification (RFID), and BT, in conjunction with online retail, may lead to inventory reductions and, consequently, lower inventory-related costs [20]. The integration of BT, IoT, and AI presents the potential to create more transparent, efficient, and secure logistics operations. These technologies can offer substantial benefits, such as increased efficiency, reduced operational costs, and enhanced transparency [1], [18].

The application of autonomous vehicles and drones in the supply chain promises great opportunities, significantly reducing human involvement in the transportation of goods across various manufacturing and service industries [13], [31]. In the Online Meal Ordering and Delivery (OMOD) sector, there is increasing consideration of drone usage, and they will inevitably be utilized in last-mile delivery [33], [35]. It is also important to note that autonomous vehicles enhance productivity in routine operations involving the movement of goods and materials within the organization itself, thereby improving safety, energy savings, operational efficiency, and increasing accuracy and consistency [33].

Digital twins in the supply chain management involve designing simulation models of all processes along the supply chain [28], from planning, production, and delivery to returns [16]. Key advantages of digital twins in the supply chain include identifying inefficiencies, optimizing logistics, improving operational efficiency through real-time monitoring, analyzing and responding to disruptions, data-driven decision-making that enhances overall performance, inventory optimization through constant stock level monitoring, reducing time required for planning and production, identifying bottlenecks, minimizing errors, and providing a detailed view of the supply chain [25], [43].

The use of robotic process automation (RPA) within the supply chain reduces the amount of manual work, which decreases employee workload, saves time, and minimizes the risk of human error. In other words, it improves business process automation. [21], [47]. RPA simplifies processes such as order management, inventory tracking, demand forecasting, supply and demand planning, and similar tasks [21], [51]. By using a single RPA tool, Kalluri [21] states that processing time was reduced by 40%, manual errors decreased by 85%, and operational costs were lowered by 30%.

Big Data Analytics (BDA) provides numerous opportunities in supply chain management, including improvements in data analytics capabilities, operational efficiency in logistics, as well as supply chain sustainability and agility [4], [38]. BDA assists all supply chain stakeholders by providing real-time access to sales data, allowing for accurate forecasting [7].

Cloud computing (CC) technology, with its features, supports the competitive challenges of supply chains through structural flexibility and adaptability. An internet platform based on CC and the digital ecosystem can serve as an "information cross-docking" point between supply chain participants. In this way, the supply chain model transforms from a traditional (linear) structure into a platform-based model with simultaneous collaboration among all partners [14]. CC-based SCM impacts organizational efficiency and the marketing performance of organizations [12].

Additive manufacturing (AM), in which 3D printing plays a crucial role, has significantly transformed product design, manufacturing, and distribution. Reducing inventory costs, backlog, obsolete products, transportation costs, and supply chain complexity are just some of the advantages of AM in SCM. The integration of AM into the supply chain introduces the possibility that, for example, retailers may produce customized products using AM [2].

In recent years, sustainability has become a buzzword, and SCM has not been excluded from this trend, often resulting in the addition of the "S" prefix to SCM, making it Sustainable Supply Chain Management (SSCM). Al Amin and Baldacci [5] state that the adoption of sustainable concepts within the framework of SCM has become an important motivator for reducing waste and moving toward a sustainable environment. Anilkumar and Sridharan [6] highlight that the performance of a sustainable supply chain can be assessed through four dimensions: economic, environmental, social, and operational performance.

Wearable technology has great potential within the supply chain [45]. Shafique et al. [45] investigated the use of smartwatches and found that a high intention to use these devices would increase collaboration in the supply chain. One of the most prominent technologies in Industry 4.0 is Augmented Reality (AR), which provides support to workers in their everyday tasks within the logistics environment [36]. Plakas et al. [36] researched the introduction of AR into the order picking process to effectively support workers. Rejeb et al. [41] identified four areas in which AR smart glasses can improve logistics and SCM: improvements in visualization, interaction, user convenience, and navigation.

To the best of our knowledge, no prior studies have combined BERTopic and bipartite graph modeling to analyze innovative technologies across defined areas of supply chain management.In the paper [17] BERTopic model was used for identification of main fields of application of digital twin technology in SCM. The similar approach was used in [48]. We believe that enriching the research methodology with solutions based on bipartite graphs will not only identify the main topics mentioned in documents, but also will allow to describe the nature and the strength of relationships between these topics and particular sub-areas or other attributes describing SCM.

4. Research methodology

The research methodology is composed of two main elements. The first component is related to problem of identification of references to predefined topics in a collection of documents. And the second ingredient should serve as a tool for analyzing relationships between topics occurring in studied documents. We decided to use zero-shot BERTopic models for identification of references to predefined topics and bipartite graph models for representing relationships between topics.

During the analysis the set of abstracts of all research papers indexed by the Scopus database and related to the "supply chain management" area which were published in the period 2010 to March 2025 was used. The total number of abstracts which met these conditions was 73509.

4.1. Zero-shot BERTopic modelling

Let's assume that **D** is a collection of documents: $\mathbf{D} = [D_1, D_2, \dots, D_d, \dots D_{|\mathbf{D}|}]$. And that the document D_d can be treated as a sequence of sentences: $\mathbf{S}^d = [S_1^d, S_2^d, \dots, S_s^d, \dots, S_{|\mathbf{S}^d|}^d]$. Also, we can presume that **T** is a list of predefined topics: $\mathbf{T} = [T_1, T_2, \dots, T_t, \dots, T_{|\mathbf{T}|}]$ which are described by labels $\mathbf{L} = [L_1, L_2, \dots, L_t, \dots, L_{|\mathbf{T}|}]$ where a label L_t describes a topic T_t. A label L_t can have a form of a single word, or a sequence of words, key-phrases or sentences.

In our research we used embedding-based methods for text analysis, and we assumed that the function $\boldsymbol{v} = embed(s)$ was used for transforming a string s into its embedding $\boldsymbol{v}$ which has a form of real-value vector.

Vector $\mathbf{V} = [\boldsymbol{v}_1, \boldsymbol{v}_2, \dots, \boldsymbol{v}_t, \dots, \boldsymbol{v}_{|\mathbf{T}|}]$ with elements $\boldsymbol{v}_t = embed(L_t)$ is composed of embeddings of labels representing predefined topics. Similarly, for every document D_d embeddings can be calculated for every sentence S_s^d comprising this document. In this way, we can form a vector $\mathbf{U}_d = [\boldsymbol{u}_1^d, \boldsymbol{u}_2^d, \dots, \boldsymbol{u}_s^d, \dots, \boldsymbol{u}_{|\mathbf{S}^d|}^d]$ with elements $\boldsymbol{u}_s^d = embed(S_s^d)$. For the research project presented here for embedding calculation the SBERT model was used [40].

For identification of references to the topic T_t in in the document D_d we use zero-shot topic modelling technique proposed in [15]. In this method a document D_d is considered as a text containing a reference to topic T_t if, for at least one sentence $S_s^d \in D_d$, the cosine similarity between $\boldsymbol{u}_s^d$ (the embedding of S_s^d) and $\boldsymbol{v}_t$ (the embedding of T_t) is greater than a predefined threshold δ. The final step of the topic analysis procedure is to create modified version of topics description (which were originally represented by labels L_t). New topic descriptions are based on the way in which sentences S_s^d were assigned to topics. Let's assume that the vector $\mathbf{Z}^t = \left[Z_1^t, Z_2^t, \ldots, Z_z^t, \ldots, Z_{|\mathbf{Z}^t|}^t\right]$ is composed of sentences from all documents which were assigned to the topic T_t. Treating the contents of every element $\mathbf{Z}^t$ as a separate document, the classical TF-IDF transformation can be used for generating the list of the most important words for every topic T_t and for calculating weights for every word from this list.

The procedure presented above was used during research process for recognition of innovative technologies discussed in abstracts and for assigning abstracts to areas existing in supply chain management.

4.2. Analysis of relationships between innovative technologies and areas of supply chain management

Let's assume that the process of identification of references to predefined topics in the collection of documents was performed twice and during the first phase references to topics $\boldsymbol{I} = \{I_1, I_2, \ldots, I_i, \ldots, I_{|\boldsymbol{I}|}\}$ were found, while during the second part of the analysis references to topics $\boldsymbol{A} = \{A_1, A_2, \ldots, A_j, \ldots, A_{|\boldsymbol{A}|}\}$ were identified[1].

After identification in abstracts references to elements of I and A, a co-occurrence matrix **G** can be created:

$$\mathbf{G} = \begin{bmatrix} g_{1,1} & \cdots & g_{1,|\boldsymbol{A}|} \\ \cdots & \cdots & \cdots \\ g_{|\boldsymbol{I}|,1} & \cdots & g_{|\boldsymbol{I}|,|\boldsymbol{A}|} \end{bmatrix} \tag{1}$$

where $g_{i,j}$ is a number of documents containing references simultaneously to topic I_i and topic A_j. Matrix **G** can be treated as a representation of the bipartite graph $\boldsymbol{B}$. For visualization of the graph $\boldsymbol{B}$ represented by the co-occurrence matrix **G** the Sankey diagram will be used.

The importance of every node was expressed by calculating its strength using the approach proposed in [8]. The strength of every element of the set $\boldsymbol{I}$ can be calculated using the formula: $strength(I_i) = \sum_{j=1}^{|\boldsymbol{A}|} \frac{g_{i,j}}{\sum_{k=1}^{|\boldsymbol{I}|} g_{k,j}}$. Similarly, for calculation of strength of elements of the $\boldsymbol{A}$ set, the following formula was used: $strength(A_j) = \sum_{i=1}^{|\boldsymbol{I}|} \frac{g_{i,j}}{\sum_{k=1}^{|\boldsymbol{A}|} g_{i,k}}$. The coefficients of strength belong to the range $[0; +1]$ and increase as the importance of a given node increases.

Next, the specificity of every node can be calculated. This measure reflects for every node its diversity of interactions to each node from the opposite set. For calculating specificity we use a method presented in [37]. Measures of specificity for elements belonging to the set $\boldsymbol{I}$ were calculated as: $specificity(I_i) = \frac{\sqrt{\sum_{j=1}^{|\boldsymbol{A}|}(g_{i,j}-\mu_i)^2}}{\mu_i\sqrt{|A|(|A|-1)}}$ where $\mu_i = \frac{1}{|\boldsymbol{A}|}\sum_{j=1}^{|\boldsymbol{A}|} g_{i,j}$. Likewise, the specificity of elements from the set $\boldsymbol{A}$ was calculated using the formula: $specificity(A_j) = \frac{\sqrt{\sum_{i=1}^{|\boldsymbol{I}|}(g_{i,j}-\mu_j)^2}}{\mu_j\sqrt{|\boldsymbol{I}|(|\boldsymbol{I}|-1)}}$ where $\mu_j = \frac{1}{|\boldsymbol{I}|}\sum_{i=1}^{|\boldsymbol{I}|} g_{i,j}$. The value of the specificity coefficient belongs to the range $[0; 1]$ and values close to 0 means low specificity (relationships with all nodes from the opposite set are similar) and values close to 1 indicate high specificity (relationships with nodes from opposite set are very diversified).

Nature of relationships between nodes belonging to two sets of a bipartite graph also can be characterized by overall coefficients: normalized mutual information (*NMI*), H_2' index and niche overlap measure.

1 During empirical part of the analysis topics I will represent various innovative technologies and topics A will describe areas of od supply chain management. But the method of analysis of relationships between topics has general character and can used for any sets of topics.

Normalized mutual information was calculated using the method presented in [9] and [27]. This approach calculates the amount of shared information between the way in which objects (documents) were assigned to topics I_i and topics A_j. In general form the $NMI(\boldsymbol{I}, \boldsymbol{A})$ can be expressed as: $\frac{2 \times M(\boldsymbol{I},\boldsymbol{A})}{H(\boldsymbol{I})+H(\boldsymbol{A})}$ where $M(\boldsymbol{I}, \boldsymbol{A})$ is mutual information about the structure of objects arisen from the assignment to topics belonging to each set and $H(\boldsymbol{I})$ and $H(\boldsymbol{A})$ is the entropy related to assignment respectively to topics from both sets. After some transformations presented in [27], the mutual information can be presented as:

$$NMI(\boldsymbol{I}, \boldsymbol{A}) = \frac{-2\sum_{i=1}^{|\boldsymbol{I}|}\sum_{j=1}^{|\boldsymbol{A}|} g_{i,j} \log \frac{g_{i,j} S}{S_i S_j}}{\sum_{i=1}^{|\boldsymbol{I}|} S_i \log \frac{S_i}{S} + \sum_{j=1}^{|\boldsymbol{A}|} S_j \log \frac{S_j}{S}} \quad (2)$$

Where $S_i = \sum_{j=1}^{|\boldsymbol{A}|} g_{i,j}$, $S_j = \sum_{i=1}^{|\boldsymbol{I}|} g_{i,j}$ and $S = \sum_{i=1}^{|\boldsymbol{I}|}\sum_{j=1}^{|\boldsymbol{A}|} g_{i,j}$.

The information about the overall specialization of nodes in a bipartite graph is also delivered by normalized Shannon entropy (H_2' index) presented in [10]. Two-dimensional Shannon entropy can be expressed as: $H_2 = -\sum_{i=1}^{|\boldsymbol{I}|}\sum_{j=1}^{|\boldsymbol{A}|} \frac{g_{i,j}}{S} \log \frac{g_{i,j}}{S}$. Next, the value is normalized using the formula: $H_2' = \frac{H_2^{max} - H_2}{H_2^{max} - H_2^{min}}$ where H_2^{max} and H_2^{min} is the maximal and the minimal value of the H_2 index for a matrix having the same size equal to the size of the matrix $\mathbf{G}$. Values of the H_2' index belong to the range $[0; 1]$ and values close to 0 inform about low specialization and values close to 1 indicate that the level of specialization is high.

The information about the structure of connections in a bipartite graph is also reflected by niche overlap measures. A niche for a given topic I_i is composed of all documents having references to topics $A_1, \ldots, A_{|A|}$ which have also references to the topic I_i. A niche for a given topic A_j is composed of all documents having references to topics $I_1, \ldots, I_{|\boldsymbol{I}|}$ which have also references to the topic A_j. The measure for niche overlap index was proposed in [26]. Its value is normalized to the range $[0; 1]$. Value equal to 0 means that niches do not overlap, whereas 1 informs about the maximum overlapping of niches.

5. Empirical results

5.1. Analysis of SCM areas

The process of analysis of areas of supply chain management started with creation of zero-shot BERTopic model representing seven areas of supply chain management with ten main keywords for every topic are presented in Fig. 1. Next, references to every topic were identified in paper abstracts. The number of papers which were classified as connected to each topic was presented in Fig. 2.

In order to eliminate the impact of the increasing trend in the number of publication, for every year in the period 2010-2025 the ratio of papers containing references to each area in all publications from a given year was calculated. The results are presented in Fig. 3.

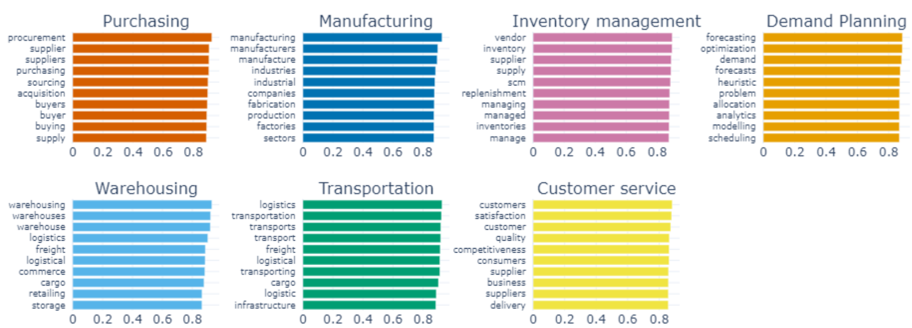

Fig. 1. Topics related to the area of supply chain management.

Fig. 2. Number of papers with references to identified areas of supply chain management over 2010-2025 period (data for 2025 calculated on the basis of papers registered in the Scopus database up to March 2025).

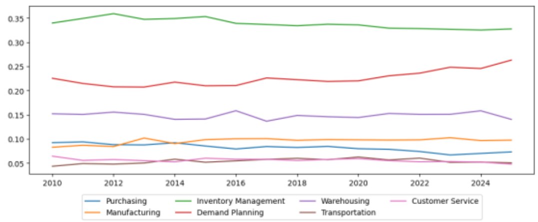

Fig. 3. The proportion of publications containing references to each SCM areas.

The results presented above indicate that the distribution of papers over topics was stable and did not change during the period analyzed. Issues connected to inventory management, demand planning and warehousing should be considered as dominant.

5.2. Analysis of innovative technologies in SCM

Analogous method was used for identification of various innovative technologies in supply chain management. The zero-shot BERTopic model for description and identification of the following innovations was built: Topic 0: Internet of Things (IoT); Topic 1: Blockchain; Topic 2: Artificial Intelligence and Machine Learning; Topic 3: Autonomous Vehicles and Drones; Topic 4: Digital Twins; Topic 5: Robotic Process Automation (RPA); Topic 6: Big Data Analytics; Topic 7: Cloud Computing; Topic 8: 3D Printing; Topic 9: Sustainability Initiatives; Topic 10: Wearable Technology. Characteristics of established topics are presented in Fig. 4.

Then, in the collection of papers analyzed, references to topics describing particular innovative technologies were identified. Number of references to specific topics occurring in each subsequent year over the period 2010-2025 is presented in Figure 5.

Calculated for each year from the period 2010-2025, the relative importance of each innovative technology in publications is shown in Figure 6.

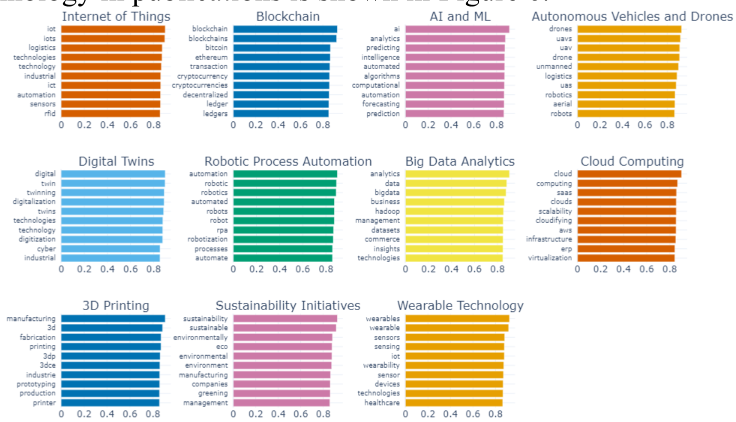

Fig. 4. Topics related to various innovative technologies in the area of supply chain management.

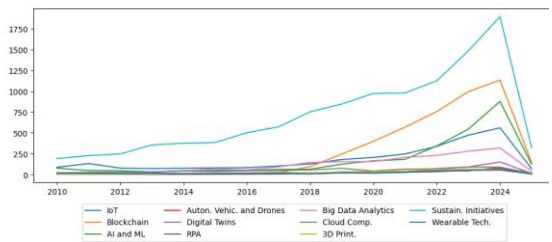

Fig. 5. Number of papers with references to identified innovative technologies occurring in the supply chain management over 2010-2025 period (data for 2025 calculated on the basis of papers registered in the Scopus database up to March 2025).

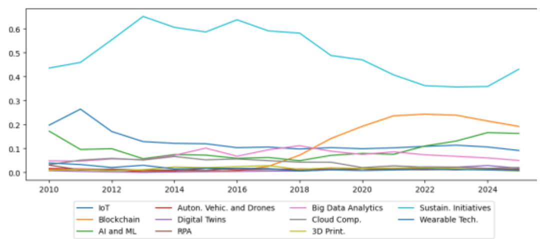

Fig. 6. The proportion of publications containing references to each innovative technology.

Innovations related to sustainable development, blockchain, artificial intelligence and machine learning should be considered the most relevant.

5.3. Analysis of relationships between innovative technologies and areas of SCM

The bipartite graph model was built for analyzing relationships between innovative technologies and areas of supply chain management. The first set of vertices consisted of established innovative technologies, while the second set of vertices included areas considered from the perspective of supply chain management. The connection between a given innovation and a given area of the supply chain management was made when references to both appeared in the same abstract. The Sankey diagram presenting the model is shown in Figure 7.

In order to precisely analyze the importance and nature of the connections of each vertex of the graph, strength and specificity measures were calculated. They were presented in the Table 1.

The results show that sustainability initiatives, blockchain, artificial intelligence and machine learning belong to the most important types of innovations which are implemented in supply chain management. On the other hand, inventory management, demand planning and warehousing should be identified as the areas most amenable to innovative changes.

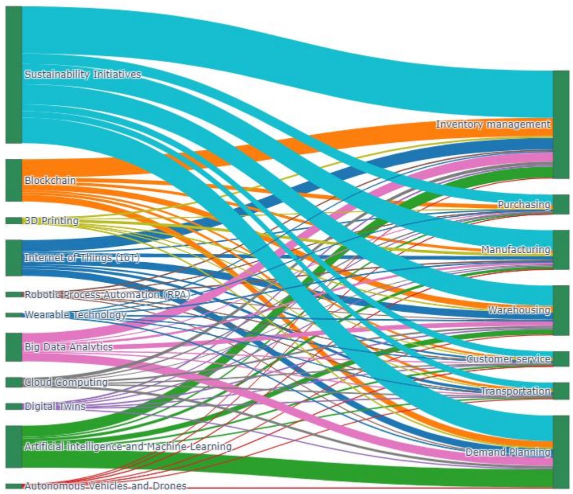

Fig. 7. Relationships between innovative technologies and main areas of supply chain management in the form of the Sankey diagram.

Table 1. Strength and specificity of vertices in the bipartite graph model.

Types of innovations			**Areas of supply chain management**		
Description	*Strength*	*Specificity*	*Description*	*Strength*	*Specificity*
Internet of Things (IoT)	0.7972	0.2793	Purchasing	0.4924	0.5188
Blockchain	0.9406	0.3559	Manufacturing	1.6804	0.4787
Artificial intelligence and Machine Learning	0.8066	0.3995	Inventory management	3.3154	0.4219
Autonomous Vehicles and Drones	0.1348	0.2457	Demand Planning	2.4346	0.3724
Digital Twins	0.1383	0.2644	Warehousing	1.8610	0.3816
Robotic Process Automation (RPA)	0.1079	0.2956	Transportation	0.7205	0.3652
Big Data Analytics	0.5577	0.3378	Customer service	0.4955	0.4221
Cloud Computing	0.2147	0.2910			
3D Printing	0.1406	0.4204			
Sustainability Initiatives	3.0669	0.2767			
Wearable Technology	0.0942	0.2356			

Specificity of various types of innovations is relatively low. It can be concluded that, with the exception of 3D printing, all other innovative technologies are used in all areas of supply chain management. Specificity of SCM areas is higher – it means that individual areas of supply chain management benefit from selected types of innovation. Network specificity is low. This fact is confirmed by all measures (normalized mutual information: 0.0242, H_2' equal to 0.0299 and niche overlap coefficients equal to 0.9499 (for SCM areas) and 0.8729 (for innovative technologies).

6. Discussion and conclusions

This research provides a novel perspective on SCM innovation through the dual lens of topic modeling and network analysis. The study systematically explores the impact of innovative technologies on various areas of SCM using BERTopic and bipartite graph modeling applied to 73,509 abstracts from the SCOPUS database. The analysis revealed insightful patterns and associations that contribute significantly to both theoretical understanding and practical applications in SCM.

The findings highlight that innovations such as sustainability initiatives, blockchain, and AI/ML dominate attention and are deeply embedded across all SCM domains. These technologies demonstrate strong applicability across multiple functions, affirming their versatility and transformative potential. The dominance of sustainability initiatives, reflected by both strength and widespread integration, aligns with the growing global emphasis on environmentally responsible operations. Blockchain's role in enhancing transparency and traceability, particularly in manufacturing and inventory management, confirms earlier research emphasizing its value in creating secure, trust-based ecosystems. Interestingly, technologies like autonomous vehicles, digital twins, RPA, and wearable technologies exhibited lower strength and specificity. This may suggest they are either in earlier stages of adoption or more specialized in their application scope. For instance, digital twins and autonomous systems are highly impactful in logistics and production environments but require substantial investment and digital maturity, possibly limiting broader acceptance. The analysis showed that most innovations had relatively low specialization across SCM domains, indicating their flexible integration. Conversely, SCM areas showed higher specificity, suggesting that certain domains (e.g., inventory management and demand planning) derive more targeted benefits from particular technologies. The low normalized mutual information and H_2' index values further confirm that the relationships between technology and SCM areas are diffuse and not concentrated, emphasizing a holistic diffusion of innovation across the supply chain spectrum. High niche overlap reinforces the notion that most innovations coexist and interact across similar SCM domains, contributing to a dynamic and interconnected innovation landscape.

In addressing RQ1, the results show that most technologies are broadly applicable across SCM domains. The bipartite graph revealed low specificity and high niche overlap, suggesting that innovations are widely shared rather than restricted to specific areas. Nevertheless, some domains, particularly inventory management, demand planning, and warehousing stood out as more frequently associated with technological innovation. In relation to RQ2, the study found that sustainability initiatives, blockchain, and AI/ML are the most influential and widely adopted technologies. These innovations exhibited high connection strength across multiple SCM areas, reflecting their growing importance in both academic and practical contexts. Overall, the results highlight that innovations in SCM are not isolated but rather integrated across domains, with certain technologies playing more central roles in shaping modern supply chains. The broad and overlapping application of innovations suggests that companies should foster cross-departmental collaboration when implementing new technologies to maximize system-wide benefits.

This study is limited to abstract-level analysis, which may not capture the full context or depth of innovation implementations. Future research could include full-text mining and case-based analysis to validate and enrich these findings. Additionally, integrating qualitative methods, such as expert interviews, could provide deeper insight into the organizational drivers behind innovation adoption. Furthermore, introduction of a hierarchical structure for innovative technologies, differentiating between broad categories (e.g., AI) and more concrete applications (e.g., predictive analytics) could provide deeper insights and improve the precision of mappings between technologies and SCM functions.

References

1. Abdelhamid, M.M., Sliman, L., Djemaa, R. Ben: AI-Enhanced Blockchain for Scalable IoT-Based Supply Chain. Logistics. 8 (4), 109 (2024)
2. Afshari, H., Searcy, C., Jaber, M.Y.: The role of eco-innovation drivers in promoting additive manufacturing in supply chains. Int J Prod Econ. 223 107538 (2020)

3. Agrawal, S., Tiwari, S.K., Singh, R.K., Kumar, K.: The impact of blockchain technology on supply chain efficiency: A review. E3S Web of Conferences. 552 1013 (2024)
4. Albqowr, A., Alsharairi, M., Alsoussi, A.: Big data analytics in supply chain management: a systematic literature review. VINE Journal of Information and Knowledge Management Systems. 54 (3), 657–682 (2024)
5. Al Amin, M., Baldacci, R.: QFD-based optimization model for mitigating sustainable supply chain management adoption challenges for Bangladeshi RMG industries. J Clean Prod. 472 143460 (2024)
6. Anilkumar E.N., Sridharan R.: Sustainable Supply Chain Management. International Journal of System Dynamics Applications. 8 (3), 15–52 (2019)
7. Arshad, F.M., Ramish, A.: The role of big data analytics in the footwear supply chains: a multiple case study perspective. Journal of Science and Technology Policy Management. (2024)
8. Bascompte, J., Melián, C.J., Sala, E.: Interaction strength combinations and the overfishing of a marine food web. Proceedings of the National Academy of Sciences. 102 (15), 5443–5447 (2005)
9. Beckett, S.J.: Improved community detection in weighted bipartite networks. R Soc Open Sci. 3 (1), 140536 (2016)
10. Blüthgen, N., Menzel, F., Blüthgen, N.: Measuring Specialization in Species Interaction Networks. BMC Ecol. 6 (1), 9 (2006)
11. Demir, S., Paksoy, T.: Artificial Intelligence, Robotics and Autonomous Systems in SCM. In: Logistics 4.0. pp. 156–165. CRC Press (2020)
12. Dong, X., Salwana, E.: The impact of cloud-based human resource and supply chain management systems on the performance of multinational organizations. Kybernetes. 51 (6), 2030–2043 (2022)
13. Eyob, E., Eyob, S.: Trends in Blockchain and Newer Technologies Uses in Logistics and Supply Chain Management. Issues In Information Systems. 20 (2), 47–55 (2019)
14. Gammelgaard, B., Nowicka, K.: Next generation supply chain management: the impact of cloud computing. Journal of Enterprise Information Management. 37 (4), 1140–1160 (2024)
15. Grootendorst, M.: BERTopic: Neural topic modeling with a class-based TF-IDF procedure, https://arxiv.org/abs/2203.05794 (2022)
16. Guo, D., Mantravadi, S.: The role of digital twins in lean supply chain management: review and research directions. Int J Prod Res. 63 (5), 1851–1872 (2025)
17. Hirata, E., Watanabe, D., Chalmoukis, A., Lambrou, M.: A Topic Modeling Approach to Determine Supply Chain Management Priorities Enabled by Digital Twin Technology. Sustainability. 16 (9), 3552 (2024)
18. Idrissi, Z.K., Lachgar, M., Hrimech, H.: Blockchain, IoT and AI in logistics and transportation: A systematic review. Transport Economics and Management. 2 275–285 (2024)
19. Ivanov, D., Tsipoulanidis, A., Schönberger, J.: Basics of Supply Chain and Operations Management. (2017)
20. Jin, S., Karki, B.: Integrating IoT and blockchain for intelligent inventory management in supply chains: A multi-objective optimization approach for the insurance industry. Journal of Engineering Research. (2024)
21. Kalluri, K.: Assessing The Impact Of Pega’s Robotic Process Automation On Supply Chain Management Efficiency. INTERANTIONAL JOURNAL OF SCIENTIFIC RESEARCH IN ENGINEERING AND MANAGEMENT. 08 (12), 1–6 (2024)
22. Kandil, T.T.: Artificial intelligence (AI) and alleviating supply chain bullwhip effects: social network analysis-based review. Journal of Global Operations and Strategic Sourcing. 18 (1), 5–35 (2025)
23. Kayıkcı, Y.: Blockchain Driven Supply Chain Management. In: Logistics 4.0. pp. 146–155. CRC Press (2020)
24. Kim, B.: Coordinating an innovation in supply chain management. Eur J Oper Res. 123 (3), 568–584 (2000)
25. Kunanets, N., Semenchuk, K., Chernova, L.: Supply chain management information

system project with the use of digital twins. In: 5th International Workshop IT Project Management (ITPM 2024). (2024)
26. Lomolino, M. V., Riddle, B.R., Brown, J.H.: Biogeography. Sinauer Associates, Sunderland
27. Mahmoudi, A., Jemielniak, D.: Proof of biased behavior of Normalized Mutual Information. Sci Rep. 14 (1), 9021 (2024)
28. Marmolejo-Saucedo, J.A., Hurtado-Hernandez, M., Suarez-Valdes, R.: Digital Twins in Supply Chain Management: A Brief Literature Review. In: Vasant, P., Zelinka, I., and Weber, G.-W. (eds.) Intelligent Computing and Optimization. pp. 653–661. Springer Nature (2020)
29. Moreira, A.C., Miguel, L., Ferreira, D.F., Zimmermann, R.A.: Innovation and Supply Chain Management. Relationship, Collaboration and Strategies, Contributions to Management Science. Springer (2018)
30. Nowicka, K.: Digital innovation in the supply chain management. Prace Naukowe Uniwersytetu Ekonomicznego we Wrocławiu. 63 (8), 202–214 (2019)
31. Odumbo, O.R., Onuma, E.P.: The future of autonomous vehicles and drones in supply chain delivery. International Journal of Science and Research Archive. 14 (1), 582–602 (2025)
32. Padma, A., Ramaiah, M.: Blockchain based solution for secure information sharing in pharma supply chain management. Heliyon. 10 (22), e40273 (2024)
33. Pagano, A.M., Liotine, M.: Technologies in supply chain management and logistics. In: Technology in Supply Chain Management and Logistics. pp. 7–35. Elsevier (2020)
34. Patalas-Maliszewska, J., Szmołda, M., Łosyk, H.: Integrating Artificial Intelligence into the Supply Chain in Order to Enhance Sustainable Production—A Systematic Literature Review. Sustainability. 16 (16), 7110 (2024)
35. Pinto, R., Zambetti, M., Lagorio, A., Pirola, F.: A network design model for a meal delivery service using drones. International Journal of Logistics Research and Applications. 23 (4), 354–374 (2020)
36. Plakas, G., Aretoulaki, E., Ponis, S.T., Agalianos, K., Maroutas, T.N.: A Proposed Technology Solution for Enhancing Order Picking in Warehouses and Distribution Centers Based on a Gamified Augmented Reality Application. In: International Conferences Interfaces and Human Computer Interaction 2020 and Game and Entertainment Technologies 2020. pp. 2017–221. (2020)
37. Poisot, T., Canard, E., Mouquet, N., Hochberg, M.E.: A comparative study of ecological specialization estimators. Methods Ecol Evol. 3 (3), 537–544 (2012)
38. Rahman, Md.A., Saha, P., Belal, H.M., Ratul, S.H., Graham, G.: Big data analytics capability and supply chain sustainability: analyzing the moderating role of green supply chain management practices. Benchmarking: An International Journal. (2024)
39. Raj, R., Singh, A., Kumar, V., Verma, P.: Challenges in adopting blockchain technology in supply chain management: a too far fetched idea? International Journal of Quality & Reliability Management. 41 (8), 2146–2180 (2024)
40. Reimers, N., Gurevych, I.: Sentence-BERT: Sentence Embeddings using Siamese BERT-Networks. In: Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP). pp. 3980–3990. Association for Computational Linguistics, Stroudsburg, PA, USA (2019)
41. Rejeb, A., Keogh, J.G., Leong, G.K., Treiblmaier, H.: Potentials and challenges of augmented reality smart glasses in logistics and supply chain management: a systematic literature review. Int J Prod Res. 59 (12), 3747–3776 (2021)
42. Rivera, L., Gauthier-Umaña, V., Chauhan, C.: Blockchain: An opportunity to improve supply chains in the wake of digitalization. International Journal of Information Management Data Insights. 4 (2), 100290 (2024)
43. Roman, E.-A., Stere, A.-S., Roșca, E., Radu, A.-V., Codroiu, D., Anamaria, I.: State of the Art of Digital Twins in Improving Supply Chain Resilience. Logistics. 9 (1), 22 (2025)
44. Sayar, A., Kurtbaş, M.C., Sancaktar, Ç., Kabak, R.D., Çakmak, Ş.: Application of Hyperledger Blockchain Technology to Logistics Supply Chain with IoT. Procedia

Comput Sci. 252 814–823 (2025)
45. Shafique, M.N., Khurshid, M.M., Rahman, H., Khanna, A., Gupta, D., Rodrigues, J.J.P.C.: The Role of Wearable Technologies in Supply Chain Collaboration: A Case of Pharmaceutical Industry. IEEE Access. 7 49014–49026 (2019)
46. Shahzadi, G., Jia, F., Chen, L., John, A.: AI adoption in supply chain management: a systematic literature review. Journal of Manufacturing Technology Management. 35 (6), 1125–1150 (2024)
47. Shamsuzzoha, A., Pelkonen, S.: A robotic process automation model for order-handling optimization in supply chain management. Supply Chain Analytics. 9 100102 (2025)
48. Srivastava, S.K., Routray, S., Bag, S., Gupta, S., Zhang, J.Z.: Exploring the Potential of Large Language Models in Supply Chain Management. Journal of Global Information Management. 32 (1), 1–29 (2024)
49. SupplyChain4Me: 7 Areas of Supply Chain, https://www.supplychain4me.com/7-areas-of-supply-chain, (2025)
50. Ünal, V., Ömürgönülșen, M., Belbağ, S., Soyasal, M.: The Internet of Things in Supply Chain Management. In: Logistics 4.0. pp. 27–34. CRC Press (2020)
51. Waduge, S., Sugathadasa, R., Piyatilake, A., Nanayakkara, S.: A Process Analysis Framework to Adopt Intelligent Robotic Process Automation (IRPA) in Supply Chains. Sustainability. 16 (22), 9753 (2024)
52. Wang, H., Chen, Y., Xie, J., Liu, C.: Research on digital empowerment, innovation vitality and manufacturing supply chain resilience mechanism. PLoS One. 20 (2), e0316183 (2025)
53. Zahid, A., Leclaire, P., Hammadi, L., Costa-Affonso, R., Ballouti, A. El: Exploring the potential of industry 4.0 in manufacturing and supply chain systems: Insights and emerging trends from bibliometric analysis. Supply Chain Analytics. 10 100108 (2025)
54. Zeng, X., Yi, J.: The supply chain information sharing path based on the internet of things. Internet Technology Letters. 7 (4), (2024)