

From Generative AI to Agentic Supply Chains: A Bibliometric and Thematic Analysis of Emerging Artificial Intelligence in Operations and Supply Chain Management

Dr. Manisha Maddel¹, Dr. Trupti M. Joshi²

¹Associate Professor, MBA/School of Business, Indira University, Pune, India

²Assistant Professor, School of Business and Management, DES Pune University, Pune, India

Manisha.maddel@indirauniversity.edu.in¹ | trupti2880@gmail.com²

Abstract – Operations and Supply Chain Management (OSCM) has changed tremendously after the usage of Artificial Intelligence (AI). There has been huge development in the field of Generative Artificial Intelligence (GenAI), Large Language Models (LLMs) and Agentic AI. It has completely reshaped the domain of Operations and Supply Chain Management (OSCM). The research paper studies and maps 203 Dimensions records under the category of Articles from 2022-2026. For the study, VOSviewer software is used to do Bibliometric analysis to examine publication growth, authors, coauthors, citations, leading sources, countries, collaborations, research fronts, intellectual foundations and thematic growth in the field. The study shows that 86.70% of the corpus was published between 2025-2026. The most productive source was International Journal of Production Research. Dmitry Ivanov is the most prolific author, and China is the leading country when cooccurrence analysis is considered. Adoption and Integration of technologies such as GenAI, LLM-enabled decision support and operational intelligence, and Disruption responsive supply chain by adapting Agentic AI is on increase in today's world. Five research fronts were shown by Bibliographic coupling. Overlay analysis shows a relative shift towards disruption management agentic applications automation digital twins and simulations. The study clearly indicates that Agentic Supply Chain is an emerging cutting-edge technology. The future research can be done on cybersecurity, resilience, multiagent coordination and human oversight.

Keywords - Generative Artificial Intelligence; Agentic AI; Large Language Models; Supply Chain Management; Bibliometric Analysis; Agentic Supply Chains

I. INTRODUCTION

Artificial intelligence (AI) has evolved from a specialised analytical capability into a general-purpose technology with the potential to influence decisions across planning, procurement, production, logistics, inventory management, risk management and supply-chain coordination. In Operations and Supply Chain Management (OSCM), earlier AI applications were largely centred on prediction, classification, optimisation and decision support. The emergence of Generative Artificial Intelligence (GenAI) and Large Language Models (LLMs) has substantially expanded this scope by enabling natural-language interaction, scenario generation, synthesis of unstructured information and conversational decision support. Richey et al. [1] described AI as potentially transformative for logistics and supply-chain management, while Wamba et al. [2], [3] highlighted both the opportunities and implementation challenges associated with GenAI and ChatGPT in OSCM.

Since 2024, research has progressively moved beyond broad discussions of GenAI potential toward more structured explanations of how and where these technologies may create operational value. Jackson et al. [4] created a capability-based framework which linked AI capabilities such as learning, perception, prediction, interaction, adaptation and reasoning with different OSCM decision areas. Dubey et al. [5] recommended a theoretical framework where GenAI-enabled OSCM was practiced. Empirical research has also initiated examining performance mechanisms. Li et al. [6], for example, coupled GenAI-enabled supply-chain management with coordination and supply-chain dynamism, Li et al. [7] also observed the relationship between GenAI usage and sustainable supply-chain performance which have hugely helped in further studies related to OSCM and Supply Chain management. These developments suggest that the literature is moving from asking whether GenAI has relevance for supply chains toward understanding how, where and under what organisational conditions it can create operational value.

An important development within this emerging research domain is the increasing use of LLMs as interfaces between unstructured information and operational decision processes. Unlike conventional analytical tools, LLMs can interpret textual information, generate alternatives, retrieve contextual knowledge and interact with decision makers using natural language. When connected with enterprise data, knowledge graphs, optimisation models, simulation systems and digital twins, LLMs have the potential to support increasingly sophisticated forms of operational intelligence. Their role therefore extends beyond content generation toward applications involving forecasting, supplier discovery, risk identification, supply-chain visibility, planning and decision support.

A more recent development is the emergence of Agentic AI, in which LLMs and related AI technologies are embedded within autonomous or semi-autonomous agents capable of pursuing goals, using tools, maintaining contextual information, coordinating with other agents and executing multi-step actions. Recent OSCM studies illustrate this emerging shift. Jannelli et al. [8] examined Agentic LLMs for autonomous multi-agent consensus seeking in supply chains, Aylak [9] investigated Agentic AI-enabled supply-chain process automation, and Ivanov [10] introduced the concept of Agentic Digital Twins combining AI-driven decision support with digital-twin capabilities. This emerging literature extends the role of AI from systems that primarily generate information or recommend decisions toward systems that may increasingly participate in planning, coordination and selected forms of operational execution.

The development of increasingly agentic systems is particularly relevant for contemporary supply chains because

OSCM environments are characterised by uncertainty, disruption, complex interdependencies and the need for rapid coordination across organisational boundaries. Agentic technologies may potentially support disruption sensing, scenario evaluation, supplier identification, logistics planning, inventory coordination and other adaptive operational activities. At the same time, greater autonomy creates new concerns regarding governance, accountability, transparency, cybersecurity, human oversight and the appropriate allocation of decision rights between human managers and artificial agents. Consequently, the development of Agentic Supply Chains cannot be understood purely as a technological transition; it also represents an emerging socio-technical and organisational challenge.

Despite the rapid expansion of this literature, its conceptual boundaries remain fragmented. GenAI, LLMs, AI agents, Agentic AI, autonomous decision-making, multi-agent systems, digital twins and AI-enabled orchestration are frequently examined through partially overlapping research streams. Existing studies have provided important insights into GenAI adoption, AI capabilities, supply-chain resilience, operational decision support and emerging autonomous applications, but the relationship between these streams has not yet been sufficiently consolidated. In particular, there is a need to understand how research concerned with broad GenAI adoption relates to LLM-enabled operational intelligence and to the more recent emergence of Agentic AI and increasingly autonomous supply-chain applications. This fragmentation across GenAI, LLM, digital-twin, autonomous-agent and multi-agent terminology provides a strong motivation for systematic mapping.

Accordingly, this study conducts a bibliometric and thematic analysis of emerging artificial intelligence in Operations and Supply Chain Management, with particular attention to the development from Generative AI and LLM-enabled applications toward Agentic AI. Rather than treating emerging AI research as a single mature domain, the study focuses on the recent 2022–2026 period and systematically examines the growth of the knowledge base, leading scholarly contributors, intellectual and collaborative structures, thematic organisation, relative thematic recency and emerging research fronts. The analysis combines bibliometric performance indicators, citation and collaboration analysis, bibliographic coupling, co-citation analysis, and VOSviewer-based term co-occurrence and overlay visualisation. The resulting evidence is used to develop an integrated interpretation of the emerging research domain and to identify future directions for responsible, adaptive and increasingly agentic supply-chain systems.

A. Research Objectives

The study has the following objectives:

1. To examine the growth of research on Generative AI, Large Language Models and Agentic AI in OSCM during 2022–2026.
2. To identify the leading journals, authors, countries and influential publications contributing to the research domain.
3. To examine the intellectual and collaborative structure of the field through citation analysis, co-authorship analysis, bibliographic coupling and co-citation analysis.
4. To identify the major thematic clusters characterising research on emerging AI in OSCM using VOSviewer term co-occurrence analysis.
5. To examine the relative thematic progression from Generative AI adoption and LLM-enabled operational intelligence toward Agentic AI and adaptive supply-chain applications.
6. To identify research gaps and develop a future research agenda for responsible, resilient and increasingly autonomous Agentic Supply Chains.

B. Research Questions

RQ1: How has research on Generative AI, Large Language Models and Agentic AI in Operations and Supply Chain Management evolved during 2022–2026?

RQ2: Which journals, authors, countries and publications have contributed most significantly to this emerging research domain?

RQ3: What intellectual and collaborative structures characterise the emerging literature on Generative AI, Large Language Models and Agentic AI in OSCM?

RQ4: What major thematic clusters characterise the literature on emerging AI in Operations and Supply Chain Management?

RQ5: How is thematic attention progressing from Generative AI adoption and LLM-enabled operational intelligence toward Agentic AI and adaptive supply-chain applications?

RQ6: What research gaps and future directions should guide the development of responsible, resilient and increasingly autonomous Agentic Supply Chains?

II. LITERATURE REVIEW

A. Generative AI in Operations and Supply Chain Management

Artificial Intelligence applications in Operations and Supply Chain Management have traditionally focused on forecasting, optimisation, pattern recognition and decision support. Generative Artificial Intelligence extends these capabilities by enabling systems to generate language, scenarios, recommendations and context-specific explanations from structured and unstructured information. This capability is particularly relevant to supply chains, where managers routinely work with heterogeneous information such as supplier communications, purchase documents, contracts, market signals, operating procedures, exception reports and disruption alerts.

The emerging literature increasingly examines GenAI from a capability and implementation perspective. Jackson et al. [4] position Generative AI as a set of capabilities that can support multiple OSCM activities including forecasting, inventory management, supply-chain design and risk management. Wamba et al. [2], [3] highlight the opportunities as well as organisational and implementation challenges associated with ChatGPT and Generative AI in OSCM. Dubey et al. [5] further connect GenAI-enabled OSCM practices with established theoretical perspectives, indicating that the implications of GenAI extend beyond technology performance to organisational capability, implementation readiness and value creation.

Empirical research has begun to examine these relationships more directly. Li et al. [6] identify coordination and supply-chain dynamism as important mechanisms in GenAI-enabled supply-chain management, while Li et al. [7] link GenAI usage with sustainable supply-chain performance. Collectively, these studies indicate that the value of Generative AI depends not merely on technology availability but on how it is integrated into organisational and inter-organisational processes.

B. Large Language Models and Operational Intelligence

Large Language Models represent an important bridge between general-purpose Generative AI capabilities and supply-chain-specific operational applications. Their ability to interpret unstructured information, interact through natural language, generate alternatives and retrieve contextual knowledge creates opportunities for applications in forecasting, procurement,

logistics, visibility, supplier management and disruption analysis.

A distinction is required between using an LLM as a conversational assistant and embedding an LLM within an operational workflow. In the latter case, language models may interact with enterprise information, analytical tools, knowledge repositories, optimisation models or simulation environments. Such integration enables LLMs to function increasingly as interfaces between complex operational information and managerial decision making.

The literature therefore indicates movement from general-purpose content generation toward operational intelligence, where the principal concern is whether LLM-generated insights can improve forecasting, coordination, risk interpretation and decision quality. However, their value depends on their integration with organisational processes and reliable information sources rather than on language-generation capability alone.

C. Agentic AI and the Emergence of Agentic Supply Chains

Agentic AI extends the Generative AI paradigm by introducing capabilities associated with goal-directed behaviour, tool use, memory, planning, adaptation and autonomous or semi-autonomous action. In a supply-chain environment, an AI agent may potentially monitor information, diagnose a problem, evaluate alternatives, interact with analytical tools or other agents, and recommend or execute selected actions.

Recent research illustrates this emerging transition. Jannelli et al. [8] examine Agentic LLMs for autonomous multi-agent consensus seeking in supply chains. Aylak [9] applies Agentic AI to supply-chain process automation with an emphasis on sustainability and cost efficiency. Ivanov [10] introduces Agentic Digital Twins that combine model-based and AI-driven decision-support capabilities for Operations and Supply Chain Management. These studies demonstrate a developing research stream in which AI is increasingly considered not only as a source of recommendations but also as a participant in iterative operational decision processes.

This transition raises significant organisational questions. When AI agents are able to initiate, coordinate or execute actions, organisations must determine appropriate decision rights, levels of autonomy and mechanisms for human intervention. Greater agent autonomy may also create concerns regarding accountability, explainability, information reliability, cybersecurity and governance.

Boone et al. [11] highlights the importance of human-AI decision making. Hendriksen [12] emphasizes that AI-enabled supply chain environment and the role human plays in it.

Agentic Supply Chain represents an upcoming and new trend in socio-technical environment in which humans and intelligent agents will interact. This interaction will not only be with humans but also enterprise systems, analytical models, digital twins and operational data along with digital twins and other agents.

D. Research Gap

The study of literature review gives insights such as though there is large development and research done in the field of Generative AI and LLM in OSCM the existing literature review remains split and fragmented across several partially overlapping fields. Agentic AI is beginning to emerge as a distinct research area. A major portion of research continues to focus on technology adoption, decision support, forecasting, coordination, operational efficiency and sustainability,

Three gaps are particularly evident.

First, the relationship among Generative AI, LLM-enabled operational intelligence and Agentic AI has not been sufficiently consolidated. These technologies are frequently examined under different terminologies even though they increasingly represent interconnected stages of AI-enabled operational capability.

Second, research remains considerably stronger in AI-supported decision making than in autonomous or semi-autonomous decision execution. Questions relating to multi-agent coordination, decision rights, human-agent collaboration, governance, accountability and end-to-end supply-chain orchestration remain comparatively underdeveloped.

Third, the rapidly growing literature lacks an integrated mapping of its scholarly contributors, intellectual structures, current research fronts, thematic clusters and relative thematic development. Without such synthesis, it is difficult to determine whether Agentic AI represents merely a new terminology or a substantively distinct emerging research frontier within OSCM.

Accordingly, a systematic bibliometric and thematic analysis is required to clarify the structure of this emerging knowledge domain, identify its principal research streams and examine how scholarly attention is extending from broad Generative AI adoption toward LLM-enabled operational intelligence and increasingly agentic supply-chain applications.

III. METHODOLOGY

A. Research Design

This study adopted a bibliometric performance-analysis and thematic-mapping design to examine the development of Generative Artificial Intelligence, Large Language Models and

Agentic AI research in Operations and Supply Chain Management (OSCM). Bibliometric performance analysis was used to assess publication growth, leading publication sources, productive authors, country contributions, citation influence and international collaboration. Network-based bibliometric techniques were further employed to examine the intellectual, collaborative and thematic structure of the research domain.

VOSviewer was used for co-authorship analysis, citation analysis, bibliographic coupling, co-citation analysis, term co-occurrence mapping and overlay visualization. Combining performance analysis with science mapping was considered appropriate for this rapidly evolving research field because performance indicators identify the principal scholarly contributors, while network and thematic analyses reveal relationships among publications, authors, countries, cited references and emerging concepts.

B. Database and Search Strategy

Bibliographic records were retrieved from Dimensions. The final search was conducted on 14 August 2026 using the Title and Abstract search fields. The search combined terminology associated with emerging forms of artificial intelligence with terminology representing Operations and Supply Chain Management.

The final Boolean search string was:

("generative AI" OR "generative artificial intelligence" OR "large language model" OR "large language models" OR "agentic AI" OR "agentic artificial intelligence" OR "AI agent" OR "AI agents")

AND

("supply chain management" OR "supply chain" OR "supply chains" OR "supply chain operations" OR "logistics management" OR "procurement management" OR "warehouse management")

The search was restricted to the Dimensions research category 3509 Transportation, Logistics and Supply Chains, the publication period 2022–2026, and the publication type Article. The year 2026 represents a partial publication year because the final database search was conducted on 14 August 2026.

C. Screening and Eligibility

The initial refined search produced 1,859 records. Application of the research-category filter reduced the dataset to 508 records. Restricting the publication period to 2022–2026 resulted in 506 records, while applying the article-only publication-type filter reduced the dataset to 245 records classified as Article.

The titles and abstracts of these 245 articles were subsequently screened for substantive relevance to the objectives of the study. Articles were included when Generative AI, Generative Artificial Intelligence, Large Language Models, AI agents, Agentic AI or closely related emerging AI technologies were materially connected with supply-chain or

operations activities such as planning, procurement, logistics, inventory, warehousing, forecasting, risk, resilience or related management processes.

Articles were excluded when OSCM terminology was merely incidental, when the study examined the supply chain of AI infrastructure rather than the application of AI within supply-chain management, when the application context was unrelated to OSCM, or when the study dealt with generic AI or machine learning without a substantive focus on the emerging AI technologies examined in this research.

Following title-and-abstract screening, 42 articles were excluded, resulting in a final corpus of 203 articles. A duplicate check based on publication titles and DOIs identified no duplicate records. The verified screening process therefore follows:

1,859 initial records → 508 research-category records → 506 records after year filtering → 245 records classified as Article → 42 excluded after relevance screening → 203 final articles.

TABLE I. INCLUSION AND EXCLUSION CRITERIA

Criterion	Inclusion	Exclusion
Publication period	2022–2026	Publications outside 2022–2026
Publication type	Records classified as Article in Dimensions	Records not classified as Article in Dimensions
Research domain	Operations, supply chain, logistics, procurement, warehousing and closely related OSCM areas	Studies in which OSCM was only incidental
AI focus	Generative AI, Generative Artificial Intelligence, LLMs, AI agents or Agentic AI	Generic AI/ML studies without substantive focus on the emerging technologies examined
Application focus	Emerging AI applied to OSCM processes, decisions, planning, forecasting, resilience, logistics, procurement or related functions	AI infrastructure supply chains, unrelated software/security applications, education and other non-OSCM applications
Screening	Title and abstract relevant to the research objectives	Title and abstract outside the defined scope

The search and screening process is summarised in Fig. 1.

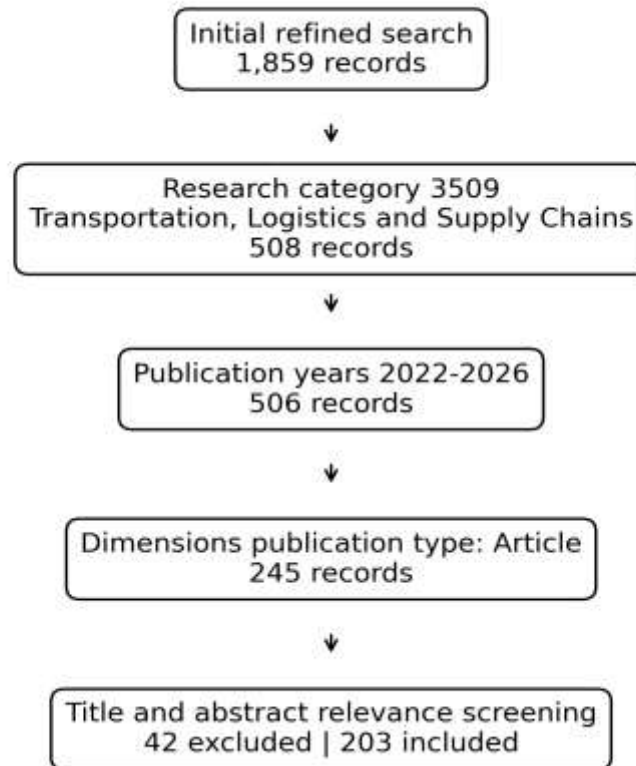


Fig. 1. Search, screening and final sample selection process.

D. Data Preparation and Cleaning

The final Dimensions dataset contained bibliographic information including publication identifiers, DOI, title, abstract, source, publication year, authors, affiliations, countries, citation counts and cited references. The dataset was reviewed before analysis to ensure consistency of publication records and suitability for VOSviewer mapping.

For text-based thematic analysis, terms were extracted from the titles and abstracts of the 203 articles. Binary counting was applied, whereby the presence of a term in a document was counted once regardless of the number of times that term appeared within the same document.

A thesaurus file was used to consolidate synonymous terminology and reduce non-substantive textual noise. For example, variants such as LLM, LLMs and large language models were consolidated under large language model; GenAI, Gen AI and generative AI were consolidated under generative artificial intelligence; SCM was standardised as supply chain management; decision was consolidated with decision making;

and logistic was standardised as logistics. Generic terms that did not represent meaningful thematic concepts were excluded from the final analysis.

For the final term co-occurrence analysis, a minimum occurrence threshold of 13 was applied. Thirty-six terms met this threshold. The qualifying terms were subsequently reviewed for thematic relevance and the final network revealed three interconnected thematic clusters. The same cleaned term structure was used to generate the network and overlay visualizations. The overlay visualization was interpreted according to the average publication year of terms and was used to examine relative thematic recency rather than to infer causal technological evolution.

E. Bibliometric and Network Analyses

Multiple complementary bibliometric analyses were conducted to examine different dimensions of the research field.

TABLE II. VOSVIEWER ANALYSES AND FINAL THRESHOLDS

Analysis	Unit of Analysis	Counting Method / Threshold	Final Network
Countries			
Country co-authorship		Full counting; minimum 3 publications	17 of 44 countries met the threshold

Analysis	Unit of Analysis	Counting Method / Threshold	Final Network
Authors			
Author co-authorship		Full counting; minimum 2 publications	41 authors met the threshold; largest connected component = 6
Documents			
Citation analysis		Minimum 10 citations	42 documents met threshold; largest connected component = 39
Term co-occurrence	Title and abstract terms	Binary counting; minimum 13 occurrences	36 terms met threshold; 3 thematic clusters
Bibliographic coupling	Documents	Full counting; minimum 5 citations	63 documents met threshold; largest connected component = 58; 5 clusters
Co-citation analysis	Cited references	Full counting; minimum 10 citations	39 of 5,971 cited references met threshold; 3 clusters

Country co-authorship analysis was conducted to examine the international collaboration structure of the field. A minimum threshold of three publications per country was applied, with 17 of the 44 countries represented in the dataset meeting the inclusion threshold. Total link strength was used to assess the extent of collaboration among countries.

Author co-authorship analysis was conducted using a minimum threshold of two publications per author. Forty-one authors met the threshold, although the largest connected component consisted of only six authors, indicating a comparatively fragmented author-level collaboration structure.

Document-level citation analysis was performed to identify influential publications and their citation relationships. Threshold of minimum 10 citations per document was considered. Of the 203 articles, 42 met the threshold, while the largest connected citation network contained 39 documents.

Bibliographic coupling was used to identify current research fronts, based on the extent to which publications shared common references. Full counting was used with a minimum threshold of five citations per document. Sixty-three documents met the threshold, and the largest connected component contained 58 documents. The resulting network consisted of five bibliographic-coupling clusters.

Co-citation analysis was used to investigate the intellectual foundations of the research domain by examining references that were cited together. The final corpus contained 5,971 cited references. With a minimum threshold of 10 citations, 39 cited references qualified for analysis and formed three interconnected co-citation clusters. Incomplete cited-reference author metadata in the Dimensions export resulted in several references being displayed as “anonymous” in VOSviewer; consequently, the analysis was interpreted primarily at the

structural level rather than through detailed attribution of every cited reference.

F. Interpretation of Networks and Research Fronts

VOSviewer cluster colours were treated as visual identifiers rather than as predetermined thematic categories. The interpretation and naming of thematic clusters and bibliographic-coupling research fronts were undertaken by examining the terms or publications contained within each cluster and identifying their dominant conceptual orientation.

For the term co-occurrence analysis, the three clusters were interpretively labelled Generative AI Adoption and Integration in Supply Chain Management, LLM-Enabled Decision Support and Operational Intelligence, and Agentic AI for Adaptive and Disruption-Responsive Supply Chains.

Similarly, the five bibliographic-coupling clusters were interpreted from the titles and thematic orientation of the documents grouped within each cluster. The resulting labels were therefore author-interpreted research-front labels and not labels automatically generated by VOSviewer.

G. Analytical Framework

The analyses were linked directly to the six research questions. Publication trends addressed RQ1; journal, author, country and citation-performance indicators addressed RQ2; co-authorship, citation networks, bibliographic coupling and co-citation analysis addressed RQ3; term co-occurrence analysis addressed RQ4; overlay visualization and emerging research fronts informed RQ5; and synthesis of the bibliometric and thematic findings was used to identify research gaps and develop the future research agenda addressing RQ6.

IV. RESULTS AND ANALYSIS

A. Annual Publication Trend

TABLE III. ANNUAL DISTRIBUTION OF PUBLICATIONS ON GENERATIVE AI AND AGENTIC AI IN OPERATIONS AND SUPPLY CHAIN MANAGEMENT

Year	Publications	Share	Cumulative
2022	3	1.48%	3

Year	Publications	Share	Cumulative
2023	9	4.43%	12
2024	15	7.39%	27
2025	87	42.86%	114
2026	89	43.84%	203

2026 represents a partial publication year because the Dimensions search was conducted on 14 August 2026.

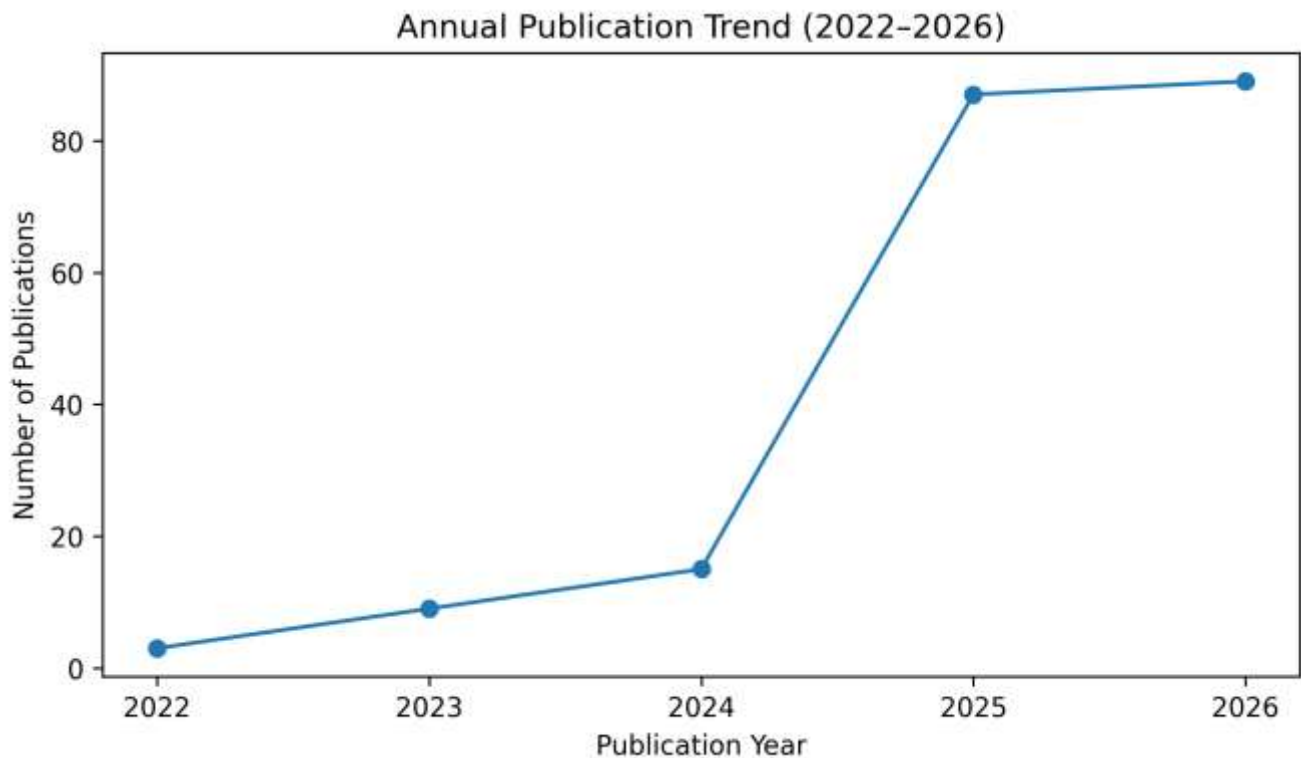


Fig. 2. Annual publication trend of research on Generative AI, Large Language Models and Agentic AI in OSCM (2022-2026).

**2026 is a partial publication year; the Dimensions search was conducted on 14 August 2026.*

The annual publication trend demonstrates a sharp increase in scholarly attention to Generative AI, Large Language Models and Agentic AI in Operations and Supply Chain Management. Publications increased from only 3 articles in 2022 to 9 in 2023 and 15 in 2024. A substantial acceleration occurred in 2025, with 87 publications, while 89 articles had already been published by 14 August 2026. Overall, 176 of the 203 articles, representing 86.70% of the final corpus, were published during 2025–2026. This rapid increase indicates that emerging artificial

intelligence applications in OSCM have developed into a highly active and fast-growing research domain. The 2026 figure should, however, be interpreted cautiously because it represents a partial publication year.

B. Leading Journals / Publication Sources

TABLE IV. LEADING PUBLICATION SOURCES IN GENERATIVE AI AND AGENTIC AI RESEARCH IN OSCM

Rank	Journal / Source	Publications	Total Citations	Average Citations per Article
1	International Journal of Production Research	15	833	55.53
2	International Journal of Production Economics	13	460	35.38
3	International Journal of Logistics Research and Applications	9	84	9.33
4	Technological Forecasting and Social Change	8	34	4.25
5	IEEE Transactions on Engineering Management	4	96	24.00
6	Applied Sciences	4	89	22.25
7	Business Strategy and the Environment	4	14	3.50

Rank	Journal / Source	Publications	Total Citations	Average Citations per Article
8	Journal of Information Systems Engineering & Management	4	1	0.25
9	Transportation Research Part E: Logistics and Transportation Review	3	316	105.33
10	Sustainability	3	53	17.67

The source analysis indicates that the literature is concentrated primarily in established production, logistics and technology-management journals. The International Journal of Production Research was the most productive source, contributing 15 articles and receiving 833 citations, followed by the International Journal of Production Economics with 13 articles and 460 citations. The International Journal of Logistics Research and Applications ranked third with nine publications. Although Transportation Research Part E: Logistics and Transportation Review contributed only three articles, these

publications accumulated 316 citations, producing the highest average citation impact among the ten leading sources at 105.33 citations per article. This suggests that the development of the field is being shaped both by high-volume production-management journals and by a smaller number of highly influential logistics publications.

C. Leading Authors

TABLE V. LEADING AUTHORS IN GENERATIVE AI AND AGENTIC AI RESEARCH IN OSCM

Rank	Author	Publications	Total Citations	Average Citations per Paper
1	Dmitry Ivanov	5	469	93.80
2	Surajit Bag	4	62	15.50
3	Samuel Fosso Wamba	3	601	200.33
4	Ilya Jackson	3	416	138.67
5	Alexandra Brintrup	3	103	34.33
6	Susmi Routray	3	56	18.67
7	Maciel M. Queiroz	2	596	298.00
8	Yogesh K. Dwivedi	2	422	211.00
9	Soumyadeb Chowdhury	2	401	200.50
10	Lixu Li	2	226	113.00

From the table it is clear that Dmitry Ivannov was the most productive contributor who had five publications and 469 citations which was followed by Surajit Bag having four publications and 62 citations.

Samuel Fosso Wamba and Ilya Jackson each contributed three publications and had 601 and 416 citations respectively. Many other authors who had only two publications also recorded high citation impact. Maciel M. Queiroz accumulated 596

citations, while Yogesh K. Dwivedi and Soumyadeb Chowdhury had 422 and 401 citations respectively. These findings indicate that scholarly influence in this emerging field is not determined solely by publication volume; a relatively small number of highly cited contributions have played an important role in shaping the research domain.

D. Country Contributions and International Collaboration

TABLE VI. LEADING COUNTRIES IN GENERATIVE AI AND AGENTIC AI RESEARCH IN OSCM

Rank	Country	Publications	Total Citations	Total Link Strength
1	China	51	519	31
2	United States	26	1,207	31
3	India	21	118	23
4	United Kingdom	19	728	33
5	France	15	1,681	21
6	Germany	12	768	11
7	Australia	9	174	7

Rank	Country	Publications	Total Citations	Total Link Strength
8	Malaysia	6	83	17
9	South Korea	5	68	14
10	Saudi Arabia	5	49	17

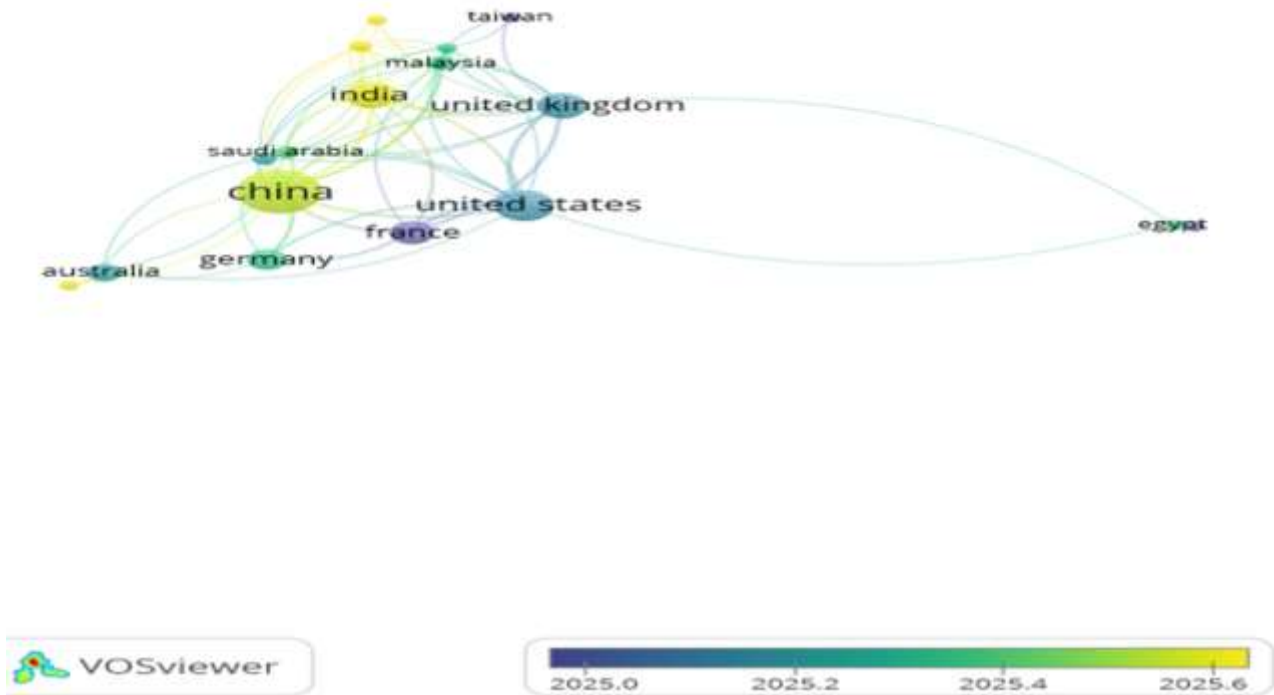


Fig. 3. Country co-authorship overlay visualization of international collaboration in Generative AI, Large Language Models and Agentic AI research in OSCM.

The country-level analysis indicates that China was the most productive contributor, with 51 publications, followed by the United States with 26, India with 21, and the United Kingdom with 19 publications. However, publication productivity differed from citation influence. France recorded the highest citation count among the leading countries, with 1,681 citations, followed by the United States with 1,207 citations and Germany with 768 citations. International collaboration was assessed through total link strength in the VOSviewer co-authorship network. The United Kingdom recorded the highest total link strength of 33, while China and the United States each recorded a total link strength of 31. India also demonstrated notable international connectivity with a total link strength of 23. These findings indicate that leadership in the field varies across

publication productivity, citation impact and international research collaboration. Using a minimum threshold of three publications per country, 17 of the 44 countries represented in the dataset met the threshold for inclusion in the VOSviewer country co-authorship network.

E. Highly Cited Publications and Citation Structure

For document-level citation analysis, a minimum threshold of 10 citations per document was applied. Of the 203 articles in the final dataset, 42 articles met the threshold, and the largest connected citation network consisted of 39 documents.

TABLE VII. TOP 10 HIGHLY CITED PUBLICATIONS

Rank	Author(s)	Year	Publication Title	Journal	Citations
1	Jackson, Ivanov, Dolgui & Namdar [4]	2024	Generative artificial intelligence in supply chain and operations management: A capability-based framework for analysis and implementation	International Journal of Production Research	407
2	Richey et al. [1]	2023	Artificial intelligence in logistics and supply chain management: A primer and roadmap for research	Journal of Business Logistics	401

Ran k	Author(s)	Year	Publication Title	Journal	Citatio ns
3	Wamba, Queiroz, Jabbour & Shi [3]	2023	Are both generative AI and ChatGPT game changers for 21st-Century operations and supply chain excellence?	International Journal of Production Economics	323
4	Wamba, Guthrie, Queiroz & Minner [2]	2023	ChatGPT and generative artificial intelligence: An exploratory study of key benefits and challenges in operations and supply chain management	International Journal of Production Research	273
5	Hendriksen [12]	2023	Artificial intelligence for supply chain management: Disruptive innovation or innovative disruption?	Journal of Supply Chain Management	188
6	Li, Zhu, Chen & Liu [7]	2024	Generative AI usage and sustainable supply chain performance: A practice-based view	Transportation Research Part E: Logistics and Transportation Review	116
7	Li, Liu, Jin, Cheng & Zhang [6]	2024	Generative AI-enabled supply chain management: The critical role of coordination and dynamism	International Journal of Production Economics	110
8	Dubey, Gunasekaran & Papadopoulos [5]	2024	Benchmarking operations and supply chain management practices using Generative AI: Towards a theoretical framework	Transportation Research Part E: Logistics and Transportation Review	108
9	Boone et al. [11]	2025	Generative AI: Opportunities, challenges, and research directions for supply chain resilience	Transportation Research Part E: Logistics and Transportation Review	92
10	Daios et al. [13]	2025	AI Applications in Supply Chain Management: A Survey	Applied Sciences	75

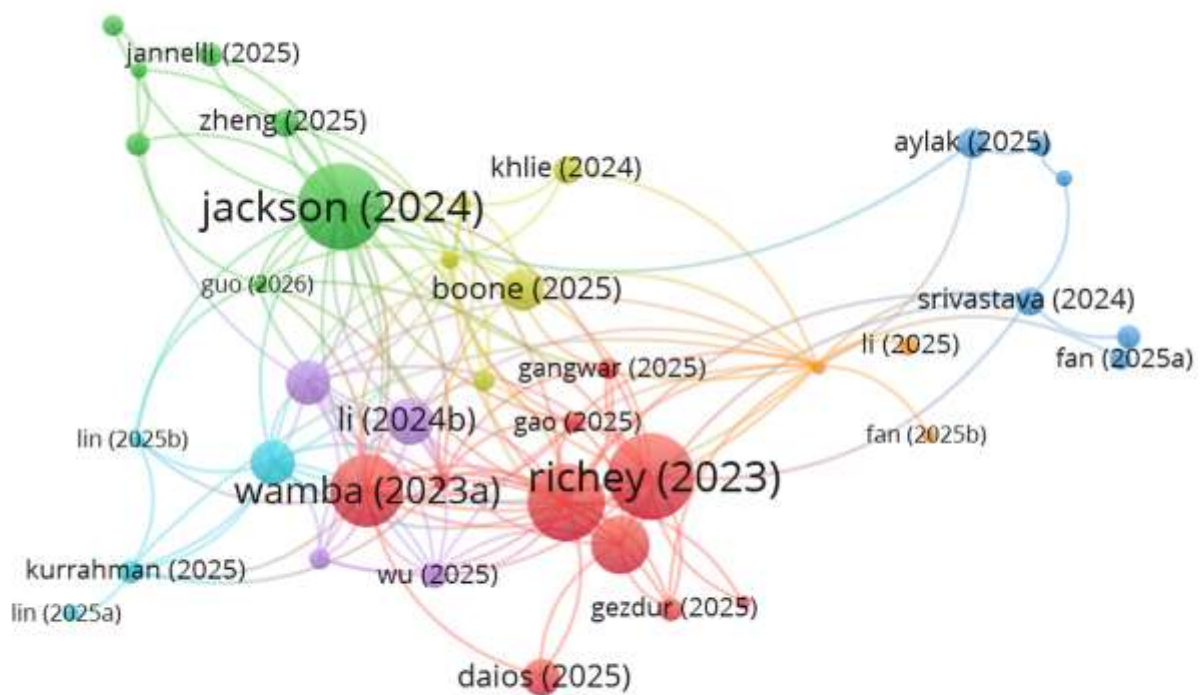


Fig. 4. Citation network of influential publications in Generative AI, Large Language Models and Agentic AI research in OSCM.

Citation analysis reveals that the intellectual development of the field is anchored by a relatively small group of highly influential publications. Jackson et al. [4] emerged as the most cited study with 407 citations, closely followed by Richey et al. [1] with 401 citations. The two studies led by Wamba in 2023 also received substantial attention, accumulating 323 and 273 citations respectively. These influential publications primarily established the early conceptual foundations for understanding Artificial Intelligence, Generative AI and ChatGPT within Operations and Supply Chain Management. Subsequent highly cited studies expanded the discussion toward sustainable supply-chain performance, coordination, resilience and operational benchmarking. The connected citation network further indicates that much of the influential literature is

intellectually interrelated, with 39 of the 42 highly cited documents forming a connected network.

F. Thematic Structure of the Literature

Term co-occurrence analysis was conducted using the titles and abstracts of the final 203 articles. Binary counting was applied in VOSviewer, together with a thesaurus file to consolidate synonymous terminology and remove generic or non-thematic terms. A minimum occurrence threshold of 13 was applied, resulting in 36 terms initially meeting the threshold. After relevance screening, synonym consolidation and removal of generic terms, the final network revealed three interconnected thematic clusters representing the major research streams within the domain.

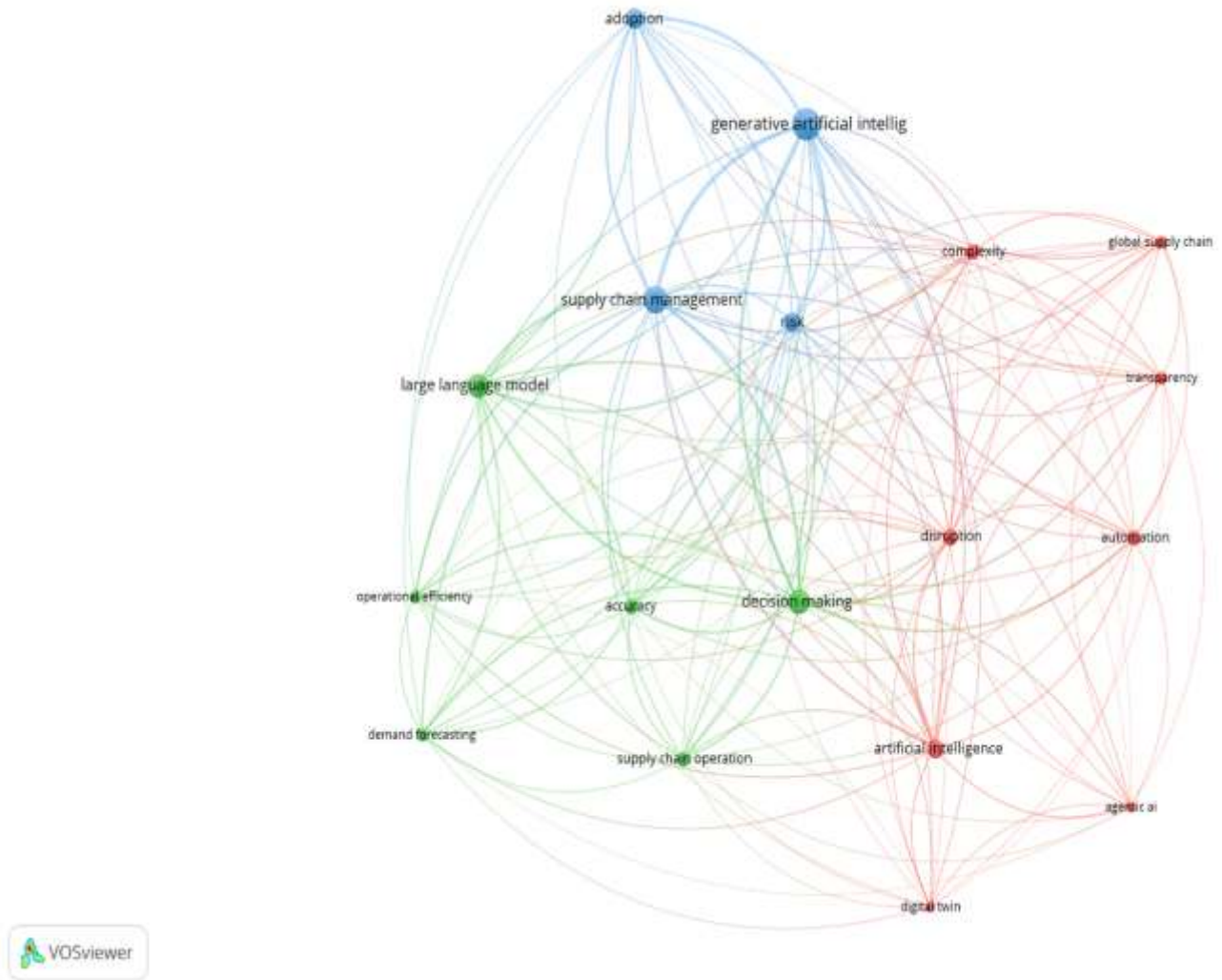


Fig. 5. Term co-occurrence network of Generative AI, Large Language Models and Agentic AI research in OSCM.

TABLE VIII. THEMATIC CLUSTERS IDENTIFIED THROUGH VOSVIEWER TERM CO-OCCURRENCE ANALYSIS

Cluster	Major terms in the cluster	Interpretive theme
Cluster 1 – Green	Generative artificial intelligence, supply chain management, adoption, integration, implementation, innovation, sustainability, efficiency	Generative AI Adoption and Integration in Supply Chain Management
Cluster 2 – Blue	Large language model, decision making, demand forecasting, operational efficiency, accuracy, supply chain operation, risk	LLM-Enabled Decision Support and Operational Intelligence
Cluster 3 – Red	Agentic AI, artificial intelligence, disruption, logistics, digital twin, automation, resilience, complexity, transparency, global supply chain	Agentic AI for Adaptive and Disruption-Responsive Supply Chains

The thematic labels were interpretively assigned by the authors based on the terms grouped within each VOSviewer-generated cluster.

The first cluster represents Generative AI Adoption and Integration in Supply Chain Management. It brings together terms such as generative artificial intelligence, supply chain management, adoption, integration, implementation, innovation, sustainability and efficiency. This cluster suggests that a substantial stream of research is concerned with how Generative AI is being introduced into supply-chain processes, how organisations adopt and integrate these technologies, and

how such adoption may contribute to operational and sustainability outcomes.

The second cluster represents LLM-Enabled Decision Support and Operational Intelligence. Terms such as large language model, decision making, demand forecasting, operational efficiency, accuracy, supply chain operation and risk indicate a more application-oriented research stream. This cluster reflects the growing use of LLM-based technologies for analytical support, forecasting, operational planning and improvement of decision quality within supply-chain activities.

The third cluster represents Agentic AI for Adaptive and Disruption-Responsive Supply Chains. Agentic AI is associated

with artificial intelligence, disruption, logistics, digital twin, automation, resilience, complexity, transparency and global supply chains. This cluster indicates an emerging research frontier in which AI is increasingly examined not only as a tool for generating information or supporting decisions, but also as a potential mechanism for more adaptive, coordinated and increasingly autonomous supply-chain activities.

Taken together, the three clusters indicate an emerging thematic progression from Generative AI adoption, through LLM-enabled operational intelligence, toward Agentic AI for adaptive and disruption-responsive supply chains.

G. Thematic Evolution and Overlay Visualization

The overlay visualization was used to examine the relative temporal development of the major themes identified through term co-occurrence analysis. VOSviewer assigns colours to terms according to their average publication year. In the present dataset, the colour scale is concentrated approximately between 2025.0 and 2025.4, reflecting the highly recent nature of research on Generative AI, Large Language Models and Agentic AI in Operations and Supply Chain Management. Therefore, the overlay visualization is interpreted as showing relative thematic recency within the corpus, rather than a long-term historical evolution.

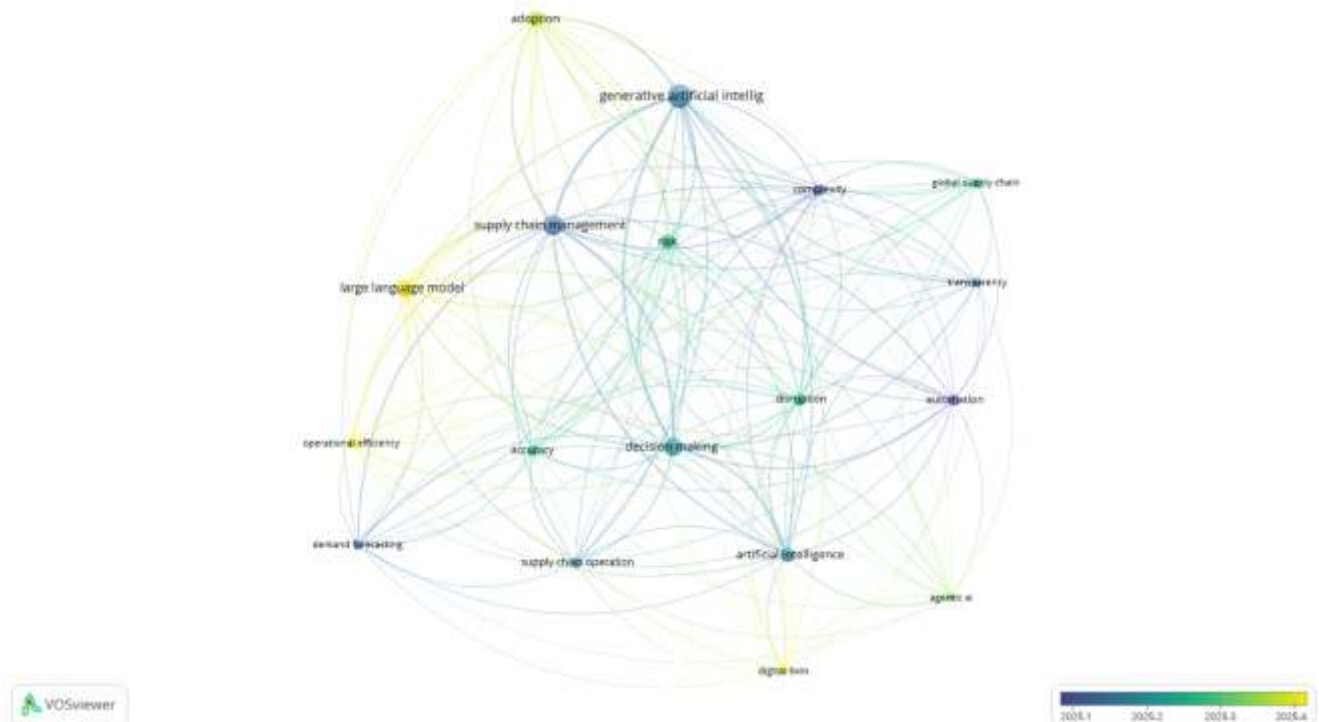


Fig. 6. Overlay visualization of relative thematic recency in Generative AI, Large Language Models and Agentic AI research in OSCM.

The overlay visualization indicates noticeable differences in the relative recency of the major research themes. Terms such as logistics, supply chain management and demand forecasting appear relatively earlier within the corpus, indicating that early studies largely connected emerging artificial intelligence technologies with established operational and supply-chain functions. Generative artificial intelligence, artificial intelligence, decision making, integration, sustainability, resilience and risk occupy the intermediate part of the temporal spectrum, reflecting the expansion of research from general AI adoption toward operational and strategic applications.

More recent attention is visible around themes such as large language model, adoption, operational efficiency, digital twin, disruption and Agentic AI. In particular, the positioning of Agentic AI among the relatively recent terms indicates that research is beginning to extend beyond AI-assisted information generation and decision support toward more adaptive, automated and potentially autonomous supply-chain applications.

When considered together with the three thematic clusters identified in the network visualization, the overlay analysis

suggests an emerging thematic progression from Generative AI adoption and LLM-enabled operational intelligence toward Agentic AI, digital-twin-enabled operations and adaptive supply-chain applications. However, this pattern represents relative thematic development within a highly recent body of literature and should not be interpreted as evidence of a direct causal or technological evolution.

Overall, the overlay visualization supports the view that Agentic AI represents an emerging research frontier within Operations and Supply Chain Management.

H. Bibliographic Coupling and Current Research Fronts

Bibliographic coupling analysis was conducted to identify the current research fronts within the literature. A minimum threshold of 5 citations per document was applied. Of the 203 articles in the final dataset, 63 documents met the threshold, and the largest connected component consisted of 58 documents. The network was generated using full counting in VOSviewer and revealed five interconnected clusters, indicating the presence of several contemporary research streams that share common intellectual foundations.

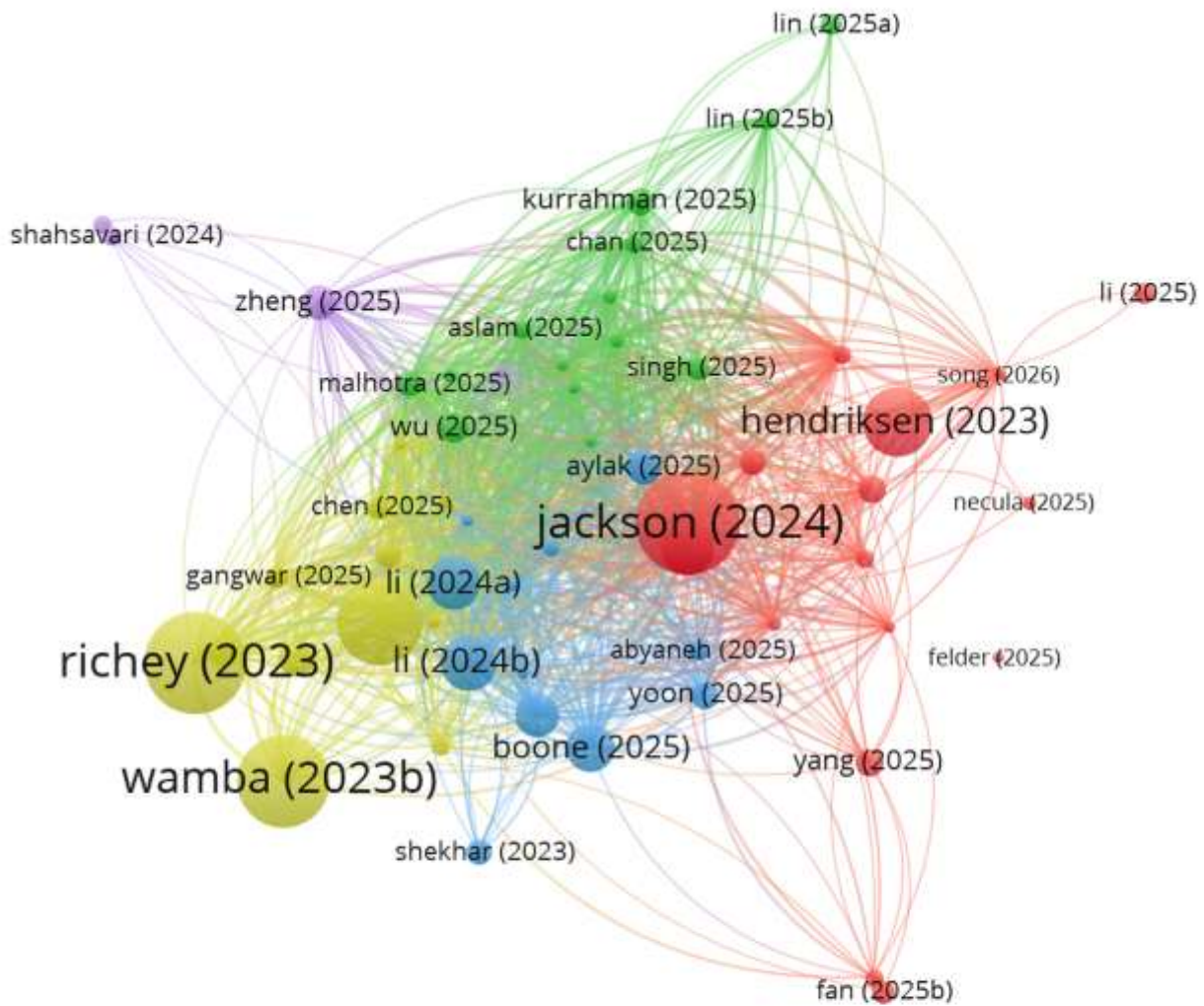


Fig. 7. Bibliographic coupling network depicting current research fronts in Generative AI and Agentic AI research in OSCM.

TABLE IX. CURRENT RESEARCH FRONTS IDENTIFIED THROUGH BIBLIOGRAPHIC COUPLING

Cluster	No. of Papers	Representative studies	Proposed research front
Cluster 1	16	Dubey et al. [5]; Jackson et al. [4], [15]; Jannelli et al. [8]; Ivanov [10]; Song et al. [14]	LLM and Agentic AI Architectures for Intelligent Supply-Chain Decision Systems
Cluster 2	14	Malhotra and Manzoor [16]; Wu et al. [17]; Bag [18]; Bag et al. [19]; Singh et al. [20]; Kurrahman et al. [21]	Generative AI-Enabled Sustainable, Flexible and Human-Centric Supply Chains
Cluster 3	12	Guo et al. [22]; Li et al. [6], [7]; Boone et al. [11]; Yoon et al. [23]; Aylak [9]	Resilience, Performance and Sustainable Supply-Chain Transformation

Cluster	No. of Papers	Representative studies	Proposed research front
Cluster 4	12	Maghroor et al. [24]; Gao et al. [25]; Gangwar et al. [26]; Chen et al. [27]; Wamba et al. [2], [3]	GenAI Adoption, Implementation Drivers and Organisational Readiness
Cluster 5	4	Akhtar et al. [28]; Zheng and Brintrup [29]; Shahsavari et al. [30]; Luo et al. [31]	LLM-Enabled Risk Sensing, Visibility and Supply-Chain Intelligence

Research-front labels were interpretively assigned by the authors after examining the titles and thematic orientation of documents grouped within each VOSviewer bibliographic-coupling cluster.

Cluster 1 – LLM and Agentic AI Architectures for Intelligent Supply-Chain Decision Systems. This cluster represents a technology- and architecture-oriented research front. It includes work on Generative AI capability frameworks, Large Language Models in supply-chain management, retrieval-augmented generation, knowledge graphs, supplier discovery, Agentic LLMs and Agentic Digital Twins. Studies such as Jackson et al. [4], Jannelli et al. [8], Ivanov [10], Song et al. [14] and Jackson et al. [15] illustrate the increasing movement toward AI systems that combine language models with enterprise information, digital representations and autonomous or semi-autonomous decision processes.

Cluster 2 – Generative AI-Enabled Sustainable, Flexible and Human-Centric Supply Chains. The second research front focuses on the organisational and sustainability implications of Generative AI. Representative studies address supply-chain flexibility, circularity, green supply-chain management, procurement applications, human-centric AI, employee-related issues and technology adoption. The cluster therefore extends GenAI research beyond technical functionality toward questions of sustainability, organisational capability, human involvement and responsible implementation.

Cluster 3 – Resilience, Performance and Sustainable Supply-Chain Transformation. This cluster concentrates on the performance consequences of emerging AI technologies. Research examines supply-chain resilience, coordination and dynamism, sustainable performance, disruption management, digital manufacturing, carbon performance and Agentic AI-enabled process automation. The presence of studies on resilience, sustainability and operational performance suggests that an important research front is shifting from asking whether GenAI can be adopted to examining how it affects measurable supply-chain outcomes and transformation.

Cluster 4 – GenAI Adoption, Implementation Drivers and Organisational Readiness. The fourth cluster brings together research on GenAI and ChatGPT adoption, implementation challenges, technology fit, behavioural drivers, organisational readiness and supply-chain performance. It also contains several influential early studies by Wamba [2], [3] and Richey et al. [1] that helped establish the broader AI and GenAI research agenda in OSCM. This cluster therefore represents the organisational adoption foundation from which more specialised applications have subsequently developed.

Cluster 5 – LLM-Enabled Risk Sensing, Visibility and Supply-Chain Intelligence. The fifth and smallest cluster is more specialised and focuses on the use of LLMs and Generative AI for supply-chain visibility, risk identification and information extraction. Its studies include news-based event identification, knowledge-graph relationship prediction, global supply-chain

risk and disinformation control, and automated carbon-footprint estimation. Although comparatively small, the cluster indicates an emerging research direction in which LLMs are used as sensing and intelligence mechanisms for complex supply-chain environments.

Overall, the bibliographic coupling analysis shows that the contemporary research landscape is no longer centred on a single question of Generative AI adoption. Instead, it is diversifying into interconnected fronts involving agentic and LLM-based architectures, sustainable and human-centric transformation, resilience and performance, organisational adoption, and AI-enabled risk sensing and visibility. This diversification reinforces the broader transition identified in the thematic analysis from general-purpose Generative AI toward increasingly specialised, operational and agentic applications in supply-chain management.

I. CO-CITATION ANALYSIS AND INTELLECTUAL FOUNDATIONS

Co-citation analysis was conducted to examine the intellectual foundations underlying the emerging literature on Generative AI, Large Language Models and Agentic AI in Operations and Supply Chain Management. The final dataset contained 5,971 cited references. A minimum threshold of 10 citations per cited reference was applied, resulting in 39 cited references meeting the threshold for inclusion in the co-citation analysis. The resulting VOSviewer network revealed three interconnected co-citation clusters, indicating that the field draws upon several related intellectual foundations rather than a single isolated knowledge base.

The most frequently co-cited references were associated with established journals in Operations and Supply Chain Management. The leading cited reference appeared in the International Journal of Production Research with 65 citations, followed by references published in the International Journal of Production Economics with 57 citations and the International Journal of Production Research with 57 citations. Other highly represented intellectual sources included Transportation Research Part E: Logistics and Transportation Review and the Journal of Business Logistics. The prominence of these journals suggests that emerging research on Generative and Agentic AI continues to build upon established foundations in production management, logistics, supply-chain strategy and technology-enabled operations.

The co-citation structure further suggests that the intellectual development of the domain integrates traditional Operations and Supply Chain Management research with newer streams concerning artificial intelligence, Generative AI, digital transformation, resilience and technology-enabled decision making. This combination provides the conceptual foundation upon which more recent research on Large Language Models and Agentic AI is developing.

A limitation was encountered in interpreting individual cited references because the Dimensions bibliometric export

displayed incomplete author metadata for a substantial proportion of cited references, resulting in several entries being labelled as “anonymous” in VOSviewer. Consequently, the co-citation analysis was retained to examine the overall intellectual structure of the field, but the co-citation network figure was not

included in the manuscript to avoid presenting potentially ambiguous reference labels.

J. Synthesis of Bibliometric Findings

TABLE X. SUMMARY OF BIBLIOMETRIC FINDINGS FOR RQ1-RQ5

Research Question	Key Findings
RQ1. How has the field evolved during 2022–2026?	It is observed that in the year 2022 there were 3 publications and in 2025 it was 87 publications and 89 publications till 14 th August 2026 this clearly indicates sharp increase in publications in this area. Between 2025–26 nearly 86.70% of the final 203 paper corpus was published which clearly indicates the rapidly growing nature in this field.
RQ2. Who are the major contributors?	The most productive resource was The International Journal of production and research. The most work or research in this work was done by the author Dmitry Ivanov. The most cited dataset publication was of Jackson et al. [4]. France had the highest Citation count, and China led the publication productivity. UK had the strongest international collaborations based on the link strength.
RQ3. What intellectual and collaborative structures characterize the field?	It was seen from the study that collaboration between authors of different countries is there. But author level collaborations remain fragmented which means collaboration exists but in small groups not large group. The document citation network diagram clearly shows that 39 papers connected are highly cited which means papers are built on one another. Bibliographic coupling shows five emerging research fields and co citations analysis projected three interconnected intellectual clusters. Thus literature is getting well connected but author collaboration remains scattered and fragmented.
RQ4. What major thematic clusters characterize the literature?	Three major thematic clusters describes the literature : (1) Generative AI (GenAI) Adoption and Integration in Supply Chain Management, (2) LLM-Enabled Decision Support and Operational Intelligence, and (3) Agentic AI for Adaptive and Disruption-Responsive Supply Chains.
RQ5. How is thematic study progressing toward Agentic AI?	Overlay analysis clearly indicates there is sharp acceptance and implementation of GenAI and LLMs, and this move is from the traditional SCM towards the adoption of these new technologies. Not only GenAI but also moving very fast to Agentic AI. Though Agentic AI is upcoming and emerging field and making its roots in SCM.

The Bibliometric results clearly signifies that artificial intelligence in OSCM and SCM has expanded on a larger level. The growth started with the broader umbrella of Artificial intelligence and then moved to Generative AI applications. It was then followed by LLM models for decision making and forecasting and operational intelligence. The major study area in recent years has been Agentic AI, resilience and disruption responsiveness supply chain management and also digital twins.

At the same time, bibliographic coupling indicates that contemporary research is diversifying into distinct but interconnected fronts involving AI architectures, sustainability, organisational adoption, resilience, performance, risk sensing and supply-chain visibility. These findings provide the empirical foundation for the Discussion section and for addressing RQ6 concerning research gaps and future directions for Agentic Supply Chains.

V. DISCUSSION

The present study examined 203 articles published between 2022 and 14 August 2026 to understand the development of Generative Artificial Intelligence, Large Language Models and Agentic AI research in Operations and Supply Chain Management (OSCM). Bibliometric and thematic analyses reveal a research domain that is expanding rapidly, while

simultaneously moving from broad discussions of Generative AI adoption toward more specific operational applications involving decision support, resilience, digital twins, automation and increasingly agentic forms of artificial intelligence. The findings are discussed below in relation to the six research questions.

A. Rapid Emergence and Growth of the Research Domain

The major findings from the study highlights that Generative AI, LLM, Agentic AI and Digital Twins have rapidly been studied and researched in the field of applications in OSCM. Out of the 203 papers studied only three were published in 2022, then nine in 2023 and fifteen in 2024 and major study in the year 2025 where 87 articles were published. And till 14th August 2026 already 89 papers were published. Thus 86.70% of the literature was published during 2025–2026.

Earlier work was more focused on understanding the implications of AI, ChatGPT, Perplexity, and Generative AI for SCM and decision-making part of operations management. As soon as these technologies became widely available research in the advanced area started which could help more in demand forecasting, procurement, sustainability, resilience and digital transformation

Agentic AI is now emerging research fields. Research is now not only about tools managing the information but also interacting and taking decision based on information. It is now focusing on coordinating tasks, supporting decision making by interacting with different systems.

Thus, RQ1 is answered by the study which explains that lot of AI research in OSCM and strong publication growth can be seen between the year 2022-2026.

B. Scholarly Contributors and the Development of the Knowledge Base

The study strongly indicates how emerging knowledge base is being shaped by analyzing the different journals, authors, countries, and good research.

The International Journal of Production Research is the most productive publication source, followed by the International Journal of Production Economics and the International Journal of Logistics Research and Applications. The study shows that AI technologies is now becoming familiar in the Operations procurement and SCM outlets. It is not just computer science topics but also helpful in application of OSCM.

Dmitry Ivanov is the most productive author other authors such as Samuel Fosso Wamba, Ilya Jackson, Maciel M. Queiroz, Yogesh K. Dwivedi and Soumya Deb Chowdhury also has very good citations influence.

From the citations and study we can say that highly dominant and empirical contributions has been made by the researchers and it is not just producing large number of papers.

The most highly cited work are of Jackson et al. [4], Richey et al. [1], Wamba et al. [2], [3], Hendriksen [12], Li et al. [6], [7] and Dubey et al. [5].

The research highly addresses the conceptual foundations and implantation implications along with opportunities and challenges of Gen AI in SCM.

Country wise China led the publications and France demonstrated the highest citations and UK had highest collaborations. The United State also had good number of citations and collaborations.

Thus RQ2 is answered by showing that emerging knowledge base is now taking shape by the help of well established journals, authors, and collaborations.

C. Intellectual and Collaborative Structure of the Field

The structural analyses reveal that the field combines relatively strong document-level intellectual connectivity with more fragmented author-level collaboration. Although 41 authors met the minimum co-authorship threshold of two publications, the largest connected author component contained only six researchers. This suggests that researcher-level collaboration remains dispersed and that stable collaborative communities around Generative AI and Agentic AI in OSCM are still developing.

In contrast, the document citation network was substantially more cohesive. Of the 42 articles meeting the minimum threshold of 10 citations, 39 formed a connected citation network. This indicates that influential studies within the field are drawn upon and responding to a relatively shared body of knowledge even though the authors themselves are not yet organised into large collaborative networks.

Bibliographic coupling provides further evidence of intellectual consolidation. Of the 63 documents meeting the minimum citation threshold for bibliographic coupling, 58 formed the largest connected component. The analysis revealed five contemporary research fronts: LLM and Agentic AI

architectures for intelligent supply-chain decision systems; Generative AI-enabled sustainable, flexible and human-centric supply chains; resilience, performance and sustainable supply-chain transformation; GenAI adoption, implementation drivers and organisational readiness; and LLM-enabled risk sensing, visibility and supply-chain intelligence.

These research fronts demonstrate that the domain is diversifying beyond broad discussions of Generative AI. The literature is increasingly developing specialised sub-streams relating to AI architectures, sustainability, organisational implementation, resilience, risk sensing, knowledge graphs, digital twins and agent-based systems.

Co-citation analysis also identified three interconnected intellectual clusters among the 39 cited references meeting the minimum threshold. Although incomplete author metadata in the Dimensions cited-reference export restricted detailed interpretation of individual co-cited works, the prominence of journals such as the International Journal of Production Research, International Journal of Production Economics, Transportation Research Part E and Journal of Business Logistics indicates that the emerging field continues to build upon established intellectual foundations in production, logistics and supply-chain management.

Overall, RQ3 is answered by showing that the field has a relatively cohesive intellectual structure but a more fragmented researcher-level collaboration structure, consistent with a domain that is expanding rapidly but remains in the process of consolidation.

D. Three Major Thematic Streams in Emerging AI Research

The term co-occurrence analysis identified three interconnected thematic clusters that provide a useful conceptual structure for understanding the emerging literature.

The first cluster, Generative AI Adoption and Integration in Supply Chain Management, represents the organisational implementation stream. Generative Artificial Intelligence, supply chain management, adoption, integration, implementation, innovation, sustainability and efficiency are the areas which focus on the organizations which have introduced Generative AI in supply chain procedures.

The second cluster shows more focus on LLM-Enabled Decision Support and Operational Intelligence, application-oriented research stream. Terms including large language models, decision making, demand forecasting, operational efficiency, accuracy, risk and supply-chain operations suggest that LLMs are increasingly used in operational intelligence tools.

These new technologies help the managers to interpret large volume of data which is in structured and unstructured format. It helps in forecasting and makes decision making faster.

The third cluster, emphasis on Agentic AI for Adaptive and Disruption-Responsive Supply Chains, and also it is most emerging field.

Agentic AI is now seen alongside concepts such as logistics, disruption, global supply chains, digital twins, automation, resilience, complexity and transparency. This point is important because now AI is helping in coordinating with other environments

Agentic systems potentially introduce capabilities such as goal-directed behaviour, autonomous task execution, tool use, coordination and adaptation to changing operational conditions. Within supply-chain environments characterised by disruptions, uncertainty and interdependent decisions, such capabilities may

have important implications for future planning and control systems.

The three clusters therefore answer RQ4 by demonstrating that the literature is organised around an emerging progression from organisational GenAI adoption, through LLM-enabled operational intelligence, toward adaptive and increasingly agentic supply-chain applications.

E. From Generative AI Toward Agentic Supply Chains

The overlay visualization provides further insight into the relative temporal development of the research themes. Because the average publication-year scale is concentrated approximately between 2025.0 and 2025.4, the map represents differences in relative recency within an extremely recent literature rather than a long historical transformation.

Themes including logistics, supply-chain management and demand forecasting appear comparatively earlier in the corpus. These represent established OSCM functions into which emerging AI technologies were initially introduced. Generative Artificial Intelligence, artificial intelligence, decision making, integration, resilience and sustainability occupy the intermediate part of the temporal spectrum.

More recent themes include Large Language Models, adoption, operational efficiency, digital twins, disruption and Agentic AI. More focus is now on Agentic AI and more precisely AI capable of interacting with different systems and environment.

The bibliographic-coupling analysis strengthens this interpretation. Recent research includes work on Agentic LLMs, multi-agent consensus seeking, Agentic Digital Twins, retrieval-augmented generation, supplier discovery, knowledge graphs and AI-based supply-chain automation. Together, these developments suggest that a new research frontier is emerging around the combination of language models, operational data, digital representations and autonomous agents.

However, this progression should not be interpreted as evidence that supply chains have already become fully autonomous. The literature is still at an early stage, and many studies remain conceptual, exploration or focused on specific applications. A more appropriate interpretation is that the field is moving toward increasingly agentic forms of supply-chain intelligence.

RQ5 is therefore answered by identifying an emerging thematic progression from Generative AI adoption → LLM-enabled operational intelligence → Agentic AI and adaptive supply-chain applications.

F. Research Gaps and the Emerging Agenda for Agentic Supply Chains

The findings reveal several important research gaps that need to be addressed before the concept of an Agentic Supply Chain can become theoretically and practically mature.

First, the current literature remains heavily concentrated on AI-assisted decision support rather than autonomous decision execution. Demand forecasting, operational efficiency, analytical support and information processing are strongly represented themes, whereas substantially less research examines situations in which AI agents independently initiate, coordinate and execute operational actions.

Future research therefore needs to investigate where the boundary between AI-supported and AI-executed supply-chain decisions should be established.

Second, multi-agent coordination remains an emerging research area. Future supply chains may involve multiple specialised agents representing procurement, production,

inventory, logistics, suppliers and customers. This creates questions regarding how these agents negotiate priorities, resolve conflicting goals, exchange information and coordinate decisions across organisational boundaries.

Third, human-agent collaboration requires substantially greater attention. Fully autonomous supply-chain systems may neither be feasible nor desirable in all decision contexts. Research needs to examine appropriate combinations of human expertise and machine autonomy, including when human approval should be mandatory and how managers can intervene when agentic decisions become inappropriate.

Fourth, the emergence of autonomous decision capabilities raises important issues relating to governance, accountability, transparency and explainability. If Agentic AI is used and agents start modifying updating deleting Inventory levels or select suppliers or also negotiate on procurement conditions or plan the transportation the responsibility of this works need to be taken care by some body or clear rules and regulations need to be defined

Fifth, there is a huge scope and opportunity in the area of Agentic AI for supply-chain resilience and disruption management. The thematic relationship between Agentic AI, disruption, resilience and global supply chains suggest strong promise for agents capable of sensing disruptions, evaluating alternatives and coordinating responses. Although there is very less proof for empirical validation in real supply-chain environments remain limited.

Sixth, Agentic Digital Twins is another important topic of research. It could dynamically help in decision making as there would be continuous updating in digital representations of SCM. Further research should take care of the risk factors associated with such real time data simulations.

Seventh, research should explore Agentic AI in areas like procurement and supplier management. Applications such as supplier fixing, negotiations, contracting, monitoring should be more focused on. These applications also create extensive ethical, legal and governance worry that need systematic investigation.

Eighth, privacy and data integrity need to be taken care, and more attention needs to be given to it. Increasing agents may result in more cyber-attacks and hacking. Manipulated data, prompt injections, compromised tools or adversarial actions could influence operational decisions with potentially significant consequences.

As seen more research on Agentic AI remains conceptual or just for study purposes. Its now time for actual implementations , experimentations and comparative case studies of operations part.

Finally, the field requires more empirical and longitudinal studies. Much of the emerging Agentic AI literature remains conceptual or exploratory.

Thus these gaps answer RQ6 and suggest that future Agentic Supply Chain research should focus not only on technological capability but also on governance, coordination, resilience, cybersecurity and empirical validation.

G. Overall Interpretation of the Emerging Research Domain

The complete analysis of bibliometric, thematic and intellectual structure strongly proposes that AI research in OSCM is undergoing a transition in technological terms as well as from research perspective. Earlier the focus of research was only how will AI or to be more specific Generative AI will be useful in SCM but now it has moved to LLMS which could do

forecasting, risk analysis supplier identification and faster decision making.

The emerging Agentic AI literature introduces a different question: to what extent can intelligent systems move from supporting decisions toward participating actively in their execution and coordination?

This change is important because it represents a potential shift in the role of artificial intelligence within supply-chain systems:

Generative AI generates information and alternatives → LLMs interpret information and support decisions → AI agents act toward defined goals → Agentic Supply Chains coordinate increasingly adaptive operational decisions.

The study therefore conceptualises an Agentic Supply Chain not as a fully autonomous supply chain without human involvement, but as an emerging operational system in which intelligent agents increasingly participate in sensing, reasoning, planning, coordinating and executing selected supply-chain activities while operating within defined human and organisational governance mechanisms.

This interpretation provides the conceptual bridge between the bibliometric findings and the future development of Agentic Supply Chains.

VI. THEORETICAL IMPLICATIONS

This study offers several theoretical contributions to the emerging literature on Artificial Intelligence in Operations and Supply Chain Management. First, it integrates three rapidly developing but often separately examined research streams—Generative Artificial Intelligence, Large Language Models and Agentic AI—within a common OSCM perspective. The bibliometric findings indicate that these technologies are not developing as completely isolated domains; rather, they form interconnected research streams concerned with organisational adoption, operational intelligence and increasingly adaptive forms of supply-chain decision making.

Second, the thematic analysis identifies a three-stage conceptual structure consisting of Generative AI Adoption and Integration, LLM-Enabled Decision Support and Operational Intelligence, and Agentic AI for Adaptive and Disruption-Responsive Supply Chains. This structure contributes to the literature by providing a systematic way of distinguishing the changing role of AI across different levels of operational involvement. Generative AI is primarily associated with information generation and organisational integration, LLMs increasingly support interpretation and operational decision processes, while Agentic AI introduces the possibility of goal-directed and increasingly autonomous action.

Third, the study extends existing discussions of digital supply chains by highlighting agency and autonomy as emerging theoretical dimensions. Traditional digital-transformation research has largely focused on connectivity, visibility, prediction and optimisation. The emerging Agentic AI literature introduces additional questions concerning whether intelligent systems can independently plan, coordinate and execute selected operational activities. This suggests that future OSCM theories may need to incorporate not only technological capability but also the degree of decision autonomy delegated to artificial agents.

Fourth, the findings indicate that resilience, disruption management, digital twins, transparency and automation are increasingly connected with Agentic AI. This provides an opportunity to extend established theories such as dynamic capabilities, information-processing theory and supply-chain resilience perspectives by examining how AI agents may

contribute to sensing, responding and reconfiguring supply-chain resources under uncertain conditions.

Fifth, bibliographic coupling reveals that the contemporary research landscape is becoming increasingly specialised, with distinct fronts around AI architectures, sustainability, organisational adoption, resilience, performance and risk intelligence. The study therefore contributes an integrative perspective that connects these fragmented research fronts and positions Agentic Supply Chains as an emerging interdisciplinary research domain at the intersection of AI, Operations Management and Supply Chain Management.

Finally, the study conceptualises an Agentic Supply Chain not as a completely autonomous system that eliminates human decision makers, but as an evolving socio-technical system in which intelligent agents increasingly participate in sensing, reasoning, planning, coordinating and executing selected supply-chain activities within defined organisational and human-governance boundaries. This conceptual distinction provides a foundation for future theoretical development and empirical investigation of different levels of AI agency within supply-chain systems.

VII. MANAGERIAL IMPLICATIONS

The findings of this study have important implications for managers responsible for operations, supply-chain planning, procurement, logistics and digital transformation. First, organisations should distinguish between the different managerial roles of Generative AI, Large Language Models and Agentic AI rather than treating them as interchangeable technologies. Generative AI can support information generation, documentation and scenario development; LLMs can assist with interpretation, forecasting and decision support; while Agentic AI may increasingly support the execution and coordination of selected operational activities.

Second, managers should adopt a progressive implementation approach. Initially the organizations may start the use of Generative AI and LLMs in activities with low risk such as supplier communication, demand analysis, retrieval and documentation and reporting. After this quality check could be done and if it is good then selected agentic applications can be introduced in the areas such as inventory updating, supplier discovery, logistic planning and disruption monitoring and decision making.

Third, Human oversight is important suggest the findings, removal of managerial control is not possible even if Greater AI is there. Thus it is important that organization define which decision AI agents may execute and which require human oversight.

High-impact decisions involving supplier selection, contract negotiation, major inventory changes or disruption-response strategies should be taken in a controlled environment and human intervention or control is needed in such cases.

Fourth, managers should establish appropriate governance and accountability structures before deploying Agentic AI in operational systems. Clear responsibility should be assigned for agent-generated decisions, system monitoring, exception handling and error correction. Organisations should also maintain audit trails that record what actions an AI agent performed, what information was used and how decisions were reached.

Fifth, successful implementation depends heavily on data quality and systems integration. Agentic AI can only make reliable operational decisions when it has access to accurate, timely and relevant information. Organisations should therefore

strengthen master-data governance, ERP integration, supply-chain visibility and real-time information capabilities before allowing intelligent agents to perform operational tasks.

Sixth, the relationship between Agentic AI and digital twins offers important managerial opportunities. Digital twins can provide AI agents with dynamic representations of supply-chain systems, allowing alternative scenarios to be evaluated before actions are implemented. Managers can therefore use agentic digital twins for disruption simulation, capacity planning, inventory decisions and logistics-network reconfiguration while maintaining appropriate human supervision.

Seventh, organisations should pay particular attention to cybersecurity and operational risk. Increasing autonomy may create new vulnerabilities if agents receive manipulated data, use compromised tools or execute incorrect actions. Access controls, validation mechanisms, cybersecurity safeguards and human override procedures should therefore be incorporated into Agentic AI implementation strategies.

Finally, managers should view Agentic AI as an augmentation and coordination technology rather than simply a replacement for human decision makers. The strongest operational value is likely to emerge when human judgement, contextual understanding and ethical responsibility are combined with the speed, analytical capacity and coordination capabilities of intelligent agents. Organisations that develop this human-agent collaboration capability may be better positioned to achieve resilient, responsive and increasingly intelligent supply-chain operations.

VIII. LIMITATIONS OF THE STUDY

This study has several limitations that should be considered while interpreting the findings.

First, the bibliometric dataset was obtained from Dimensions only. Although Dimensions provides broad bibliographic coverage and supports VOSviewer-compatible exports, the exclusion of other databases such as Scopus or Web of Science may have resulted in some relevant publications being omitted.

Because inclusion used the Dimensions document-type filter, source-level venue labels may occasionally differ from conventional journal/proceedings classifications; the study therefore reports the corpus as records classified as Article in Dimensions.

Second, the study focused on records classified as Article by Dimensions during 2022–2026. The year 2026 represents only a partial publication year because the database search was conducted on 14 August 2026. Therefore, publication counts for 2026 should not be interpreted as directly comparable with complete calendar years.

Third, the final sample was restricted to 203 articles selected after title-and-abstract checking. Depending upon research scope some articles were removed, and researcher decision was taken into consideration.

Fourth, the fields Generative AI, Large Language Models, AI agents and Agentic AI are evolving rapidly. So after this study there are chances of change in thematics changes.

Fifth, VOSviewer analysis majorly depend on choices such as minimum occurrence thresholds, citation thresholds, counting methods and thesaurus-based term consolidation.

Even though these settings were applied consistently and documented transparently, alternative parameter choices may produce somewhat different network structures.

Sixth, It is seen that citations based indicators favor publications that have more citations and so more recent

publication with less citations may appear less influential than older studies.

Seventh, in the co-citation analysis several cited reference metadata in the Dimensions export appeared as “anonymous” in VOSviewer, which made it difficult to give detailed report of individual intellectual foundations and prevented inclusion of the co-citation network as main figure in the paper.

Finally, bibliometric analysis identifies structural and thematic patterns in the literature but does not directly evaluate the effectiveness of Agentic AI in real supply-chain environments. Future research should therefore complement bibliometric findings with empirical studies, field experiments, case studies and longitudinal investigations examining the actual operational consequences of increasingly autonomous AI systems.

IX. CONCLUSION

This study provides a bibliometric and thematic examination of the emerging literature on Generative Artificial Intelligence, Large Language Models and Agentic AI in Operations and Supply Chain Management. Based on a final corpus of 203 articles published between 2022 and 14 August 2026, the analysis demonstrates that this research domain has expanded rapidly, particularly during 2025–2026, while simultaneously becoming more specialised in its technological and operational focus.

The findings show that the field is developing around three major thematic streams: Generative AI Adoption and Integration in Supply Chain Management, LLM-Enabled Decision Support and Operational Intelligence, and Agentic AI for Adaptive and Disruption-Responsive Supply Chains. Bibliographic coupling further identified five contemporary research fronts relating to intelligent AI architectures, sustainability and human-centric supply chains, resilience and performance, organisational adoption, and AI-enabled risk sensing and visibility.

The combined thematic and overlay analyses indicate an emerging progression from the use of Generative AI for information generation and organisational integration, toward Large Language Models for operational intelligence and decision support, and increasingly toward Agentic AI systems capable of participating in goal-directed operational activities. This progression should not be interpreted as evidence that fully autonomous supply chains have already emerged. Rather, it indicates a developing research frontier in which AI systems are being assigned progressively greater roles in sensing, reasoning, planning, coordination and selected forms of execution.

A central contribution of this study is therefore the positioning of the Agentic Supply Chain as an emerging socio-technical system in which intelligent agents may increasingly interact with supply-chain data, digital twins, enterprise systems and human decision makers to support adaptive operational responses. Human oversight, accountability and organisational governance remain essential components of such systems.

The study also reveals that the field remains theoretically and empirically immature in several areas. Questions concerning multi-agent coordination, human-agent collaboration, autonomous decision boundaries, governance, cybersecurity, explainability and real-world operational performance require substantially greater investigation. Future research should therefore move beyond conceptual demonstrations toward empirical studies capable of evaluating when, where and under what governance conditions agentic technologies create sustainable operational value.

Overall, the evidence suggests that the next stage of AI-enabled Operations and Supply Chain Management will not be defined merely by the ability of artificial intelligence to generate information, but increasingly by its capacity to interpret operational environments, coordinate decisions and act toward defined supply-chain objectives. Understanding how this transition can occur responsibly, securely and effectively represents an important research agenda for the development of future Agentic Supply Chains.

REFERENCES

- [1] R. G. Richey, S. Chowdhury, B. Davis-Sramek, M. Giannakis, and Y. K. Dwivedi, "Artificial intelligence in logistics and supply chain management: A primer and roadmap for research," *Journal of Business Logistics*, vol. 44, no. 4, pp. 532-549, 2023. <https://doi.org/10.1111/jbl.12364>
- [2] S. F. Wamba, C. Guthrie, M. M. Queiroz, and S. Minner, "ChatGPT and generative artificial intelligence: An exploratory study of key benefits and challenges in operations and supply chain management," *International Journal of Production Research*, vol. 62, no. 16, pp. 5676-5696, 2023. <https://doi.org/10.1080/00207543.2023.2294116>
- [3] S. F. Wamba, M. M. Queiroz, C. J. C. Jabbour, and C. Shi, "Are both generative AI and ChatGPT game changers for 21st-century operations and supply chain excellence?" *International Journal of Production Economics*, vol. 265, 109015, 2023. <https://doi.org/10.1016/j.ijpe.2023.109015>
- [4] I. Jackson, D. Ivanov, A. Dolgui, and J. Namdar, "Generative artificial intelligence in supply chain and operations management: A capability-based framework for analysis and implementation," *International Journal of Production Research*, vol. 62, no. 17, pp. 6120-6145, 2024. <https://doi.org/10.1080/00207543.2024.2309309>
- [5] R. Dubey, A. Gunasekaran, and T. Papadopoulos, "Benchmarking operations and supply chain management practices using Generative AI: Towards a theoretical framework," *Transportation Research Part E: Logistics and Transportation Review*, vol. 189, 103689, 2024. <https://doi.org/10.1016/j.tre.2024.103689>
- [6] L. Li, Y. Liu, Y. Jin, T. C. E. Cheng, and Q. Zhang, "Generative AI-enabled supply chain management: The critical role of coordination and dynamism," *International Journal of Production Economics*, vol. 277, 109388, 2024. <https://doi.org/10.1016/j.ijpe.2024.109388>
- [7] L. Li, W. Zhu, L. Chen, and Y. Liu, "Generative AI usage and sustainable supply chain performance: A practice-based view," *Transportation Research Part E: Logistics and Transportation Review*, vol. 192, 103761, 2024. <https://doi.org/10.1016/j.tre.2024.103761>
- [8] V. Jannelli, S. Schöpf, M. Bickel, T. Netland, and A. Brintrup, "Agentic LLMs in the supply chain: Towards autonomous multi-agent consensus-seeking," *International Journal of Production Research*, ahead-of-print, pp. 1-31, 2025. <https://doi.org/10.1080/00207543.2025.2604311>
- [9] B. L. Aylak, "SustAI-SCM: Intelligent supply chain process automation with Agentic AI for sustainability and cost efficiency," *Sustainability*, vol. 17, no. 6, 2453, 2025. <https://doi.org/10.3390/su17062453>
- [10] D. Ivanov, "Agentic digital twins: Bridging model-based and AI-driven decision-making support for a new era of supply chain and operations management," *International Journal of Production Research*, vol. 64, no. 15, pp. 6574-6590, 2026. <https://doi.org/10.1080/00207543.2026.2630277>
- [11] T. Boone, B. Fahimnia, R. Ganeshan, D. M. Herold, and N. R. Sanders, "Generative AI: Opportunities, challenges, and research directions for supply chain resilience," *Transportation Research Part E: Logistics and Transportation Review*, vol. 199, 104135, 2025. <https://doi.org/10.1016/j.tre.2025.104135>
- [12] C. Hendriksen, "Artificial intelligence for supply chain management: Disruptive innovation or innovative disruption?" *Journal of Supply Chain Management*, vol. 59, no. 3, pp. 65-76, 2023. <https://doi.org/10.1111/jscm.12304>
- [13] A. Daios, N. Kladovasilakis, A. Kelemis, and I. Kostavelis, "AI applications in supply chain management: A survey," *Applied Sciences*, vol. 15, no. 5, 2775, 2025. <https://doi.org/10.3390/app15052775>
- [14] Z. Song, Y. Xie, L. Yang, and Y. Zhao, "Large language models in supply chain management: A systematic literature review and application framework," *International Journal of Production Research*, vol. 64, no. 16, pp. 7144-7184, 2026.
- [15] I. Jackson, M. J. Saénz, D. Ivanov, and B. Jun, "Supply chain mapping through retrieval-augmented generation: Applications to the electronics industry," *Journal of the Operational Research Society*, vol. 77, no. 7, pp. 1798-1818, 2026.
- [16] G. Malhotra and R. Manzoor, "Generative artificial intelligence adoption for achieving supply chain efficiency, circularity and sustainability," *Journal of Enterprise Information Management*, vol. 39, no. 2, pp. 736-758, 2025.
- [17] H. Wu, G. Li, and D. Ivanov, "The transformative power of generative AI for supply chain management: Theoretical framework and agenda," *IEEE Transactions on Engineering Management*, vol. 12, no. 2, pp. 425-433, 2025.
- [18] S. Bag, "From prompts to performance: How generative AI is reshaping supply chain flexibility," *Global Journal of Flexible Systems Management*, vol. 27, suppl. 1, pp. 1-22, 2025.
- [19] S. Bag, M. S. Rahman, S. Routray, and V. R. Sreedharan, "Human-centric generative AI in circular supply chains: Theoretical insights from ethics, dynamic capabilities, and resource conservation," *Business Strategy and the Environment*, vol. 35, no. 4, pp. 5000-5029, 2025.
- [20] V. Singh, L. Hughes, M. A. Albashrawi, I. Jeon, and Y. K. Dwivedi, "Generative artificial intelligence (GenAI) in procurement and supply chain management: Applications, opportunities and challenges," *Journal of Systems and Information Technology*, vol. 28, no. 1, pp. 123-144, 2025.
- [21] T. Kurrahman, F. M. Tsai, M. K. Lim, K. Sethanan, and M.-L. Tseng, "Generative AI capabilities for green supply chain management improvement: Extended dynamic capabilities view," *International Journal of Logistics Research and Applications*, vol. 29, no. 5, pp. 605-632, 2025.
- [22] J. Guo, F. Jia, and L. Chen, "How generative AI adoption affects supply chain resilience: An operations and supply chain management perspective," *Technological Forecasting and Social Change*, vol. 224, 124446, 2026.
- [23] J. Yoon, R. Alkhudary, S. Talluri, and P. Fnis, "Risk management and macroeconomic disruptions in supply chains: The role of blockchain, digital twins, generative AI, and quantum computing," *IEEE Transactions on Engineering Management*, vol. 72, pp. 2995-3009, 2025.
- [24] H. R. Maghroor, F. Madanchi, and T. O'Neal, "Leveraging generative AI for sustainable supply chain: Adoption

- challenges and strategic insights,” *Production Planning & Control*, ahead-of-print, pp. 1-20, 2025.
- [25] C. Gao, K.-H. Keoy, and A.-F. Lim, “Adoption and impact of generative artificial intelligence on blockchain-enabled supply chain efficiency,” *Journal of Systems and Information Technology*, vol. 27, no. 2, pp. 173-196, 2025.
- [26] H. Gangwar, M. Shameem, S. Patel, A. Koohang, and A. Sharma, “Understanding determinants of GenAI usage and its effect on SCM performance using dynamic capability view,” *Industrial Management & Data Systems*, vol. 125, no. 3, pp. 1110-1133, 2025.
- [27] J. Chen, J. Dai, T. Yu, and C. Wang, “Factors influencing the adoption of generative AI in supply chain management: An empirical study based on task-technology fit and the theory of planned behaviour,” *International Journal of Logistics Research and Applications*, ahead-of-print, pp. 1-22, 2025.
- [28] P. Akhtar, T. Papadopoulos, H. Khan, A. M. Ghouri, S. Shamim, and A. Ashraf, “Risk, generative AI, disinformation control, global supply chains, and social impacts,” *Technological Forecasting and Social Change*, vol. 226, 124609, 2026.
- [29] G. Zheng and A. Brintrup, “Enhancing supply chain visibility with generative AI: An exploratory case study on relationship prediction in knowledge graphs,” *International Journal of Production Research*, ahead-of-print, pp. 1-23, 2025.
- [30] M. Shahsavari, O. K. Hussain, M. Saberi, and P. Sharma, “Event identification for supply chain risk management through news analysis by using large language models,” *The Review of Socionetwork Strategies*, vol. 18, no. 2, pp. 255-278, 2024.
- [31] B. Luo, J. Liu, Z. Deng, C. Yuan, Q. Yang, L. Xiao, Y. Xie, F. Zhou, W. Zhou, and Z. Liu, “AutoPCF: A novel automatic product carbon footprint estimation framework based on large language models,” *Proceedings of the AAAI Symposium Series*, vol. 2, no. 1, pp. 102-106, 2024.