12th International Conference on Business Economics, Marketing & Management Research (BEMM-2025)
Proceedings Book Series -PBS-Vol 22, pp.61-71

Generative Artificial Intelligence in Supply Chain Management: A Bibliometric Analysis and Systematic Review

Mariem MRAD[#1], Younes BOUJELBENE[*2]

[#]*Laboratory of Economics and Management*
Faculty of Economics Sciences and Management of Sfax University of Sfax, Tunisia
[1]mariemmradin@gmail.com
[2]younes.boujelbene@gmail.com

Abstract

Supply Chain Management (SCM) is increasingly challenged by dynamic markets, demand volatility, and supply chain disruptions. Traditional approaches, while foundational, often lack adaptability to real-time data and predictive precision. Generative Artificial Intelligence (GAI), with its capabilities in data synthesis, scenario generation, and predictive optimization, offers transformative potential for SCM. However, challenges such as data dependency, model interpretability, and ethical concerns hinder its adoption. This paper conducts a bibliometric analysis and systematic review of GAI applications in SCM, mapping publication trends, methodological approaches, and emerging research themes. By analyzing 11 articles from major databases (2014–2024), we identify a surge in conceptual frameworks and exploratory studies, particularly in demand forecasting and risk management. The study highlights the need for empirical validations, ethical guidelines, and cross-industry collaborations to advance GAI integration in SCM. Insights from this review aim to guide researchers and practitioners in leveraging GAI to enhance supply chain resilience, efficiency, and sustainability.

Keywords

Generative AI, Supply Chain Management, Bibliometric Analysis, Predictive Analytics, Risk Management, Decision-Making

1. Introduction

Supply Chain Management (SCM) is a critical function in modern organizations, encompassing the planning, execution, and control of activities related to the flow of goods, information, and finances from suppliers to end consumers (Christopher, 2016). Efficient and resilient supply chains are essential for maintaining competitiveness, meeting customer demands, and navigating the complexities of the global marketplace. Traditional SCM relies on established methodologies, including statistical forecasting, optimization algorithms, and simulation models (Shapiro, 2007). However, these approaches often face limitations in adapting to rapidly changing market conditions, unforeseen disruptions, and the increasing volume and velocity of data in

ISSN: 2961-6611

contemporary supply chains (Ivanov et al., 2019).

In response to these challenges, Generative Artificial Intelligence (GAI) has emerged as a transformative technology with the potential to revolutionize SCM practices. GAI encompasses a range of machine learning techniques capable of generating new data instances, predicting future events, and optimizing complex processes (Goodfellow et al., 2020). Applications of GAI in SCM include enhanced demand forecasting, automated risk assessment, personalized customer service, and the design of more sustainable supply chain networks (Zhang et al., 2023). While GAI offers significant opportunities for improvement, its integration into SCM also presents challenges related to data quality, model interpretability, ethical considerations, and the need for skilled personnel (Bengio et al., 2021).

The application of AI in SCM is not a novel concept; earlier iterations of machine learning focused on improving predictive accuracy and automating routine tasks (Fildes et al., 2008). However, advancements in deep learning, natural language processing, and generative modeling have expanded the scope and potential of AI in SCM. Recent research has explored the use of GAI to generate synthetic data for training machine learning models, simulate supply chain disruptions to assess resilience, and create personalized recommendations for supply chain partners (Kar et al., 2023).

Although recent studies have examined the application of AI in various aspects of SCM, a comprehensive bibliometric analysis of the specific role of Generative AI is lacking. Existing reviews often focus on traditional machine learning techniques or specific application areas, without providing a holistic overview of the research landscape. For example, Choi et al. (2021) investigated AI-driven demand forecasting, but did not specifically address the contributions of generative models. Similarly, Ivanov and Dolgui (2022) explored supply chain resilience through AI, but provided limited insights into the application of GAI in predictive scenario planning.

To address this gap, this paper presents a bibliometric analysis of the existing literature on Generative Artificial Intelligence in Supply Chain Management. This study aims to systematically review the published research, identify key trends and themes, and highlight future directions for research and practice. Specifically, the study seeks to answer the following research questions:

- *How has the publication trend of GAI in SCM evolved over time?*
- *What are the key research areas and applications of GAI in SCM addressed in the literature?*
- *What are the major benefits, challenges, and future research directions identified in the literature regarding the integration of GAI in SCM?*

To address the objectives of this research, this paper is structured as follows: Section 2 outlines the research methodology, including the search strategy, data collection process, and bibliometric analysis techniques employed. Section 3 presents the results of the analysis, focusing on publication trends, leading journals, key research areas, and emerging themes. Section 4 discusses the implications of the findings for researchers and practitioners. Finally, Section 5 concludes the

ISSN: 2961-6611

paper by summarizing the key contributions and identifying future research opportunities.

2. Research Methodology

2.1. Defining and Combining the Relevant Keywords

Our research methodology emphasizes a systematic approach to keyword selection and synthesis, forming the foundation for a comprehensive bibliometric analysis. This process began with a thorough examination of keywords prevalent in leading academic publications within the domains of both Generative Artificial Intelligence (GAI) and Supply Chain Management (SCM). Guided by established research strategies in bibliometric analysis and systematic literature reviews, we selectively reviewed top-ranked journals and conference proceedings in these fields, as identified by recognized academic indices. The primary objective was to identify and analyze research focused on the integration of GAI within SCM to enhance forecasting accuracy, decision-making capabilities, and overall operational efficiency.

To capture the core concepts of our research, we identified a set of primary keywords related to "integration" and related concepts. This set included: ("integrat*" OR "combinat*" OR "synergy" OR "confluence" OR "fusion"). To ensure a comprehensive search, we also developed keyword strings covering fundamental concepts in SCM and GAI, using a combination of subject-specific terms and broader technology descriptors. The SCM-related keywords included: ("supply chain management" OR "logistics" OR "inventory management" OR "demand forecasting" OR "procurement optimization"). The GAI-related keywords encompassed: ("generative artificial intelligence" OR "deep learning" OR "machine learning" OR "neural networks" OR "large language models" OR "foundation models").

Using a logical combination of these keywords through 'AND' and 'OR' operators, we constructed various keyword strings to comprehensively examine the intersection of GAI and SCM. For instance, one search string combined "supply chain management" AND "generative artificial intelligence" to identify articles explicitly addressing this intersection. This strategic approach ensured a targeted yet extensive exploration of how GAI methodologies contribute to optimizing supply chain processes, enhancing predictive analytics, and introducing innovative computational strategies.

2.2. Research Database

To identify relevant articles, we utilized *Web of Science* which allow for filtering by titles, keywords, and abstracts, enabling us to effectively refine our dataset. The selection of databases was guided by their coverage of leading journals in both SCM and GAI, as well as their advanced search capabilities. Table 1 presents the sources used in our research, along with the initial number of records retrieved from each source.

ISSN: 2961-6611

Table 1. Overview of Data Sources

Source	Title or Abstract Count	Full Text Count
Web of Science	13	4,763

2.3. Defining Filters and Selection Criteria

To ensure methodological rigor and relevance, a systematic three-stage filtering process was implemented, as outlined in Table 2. Initially, the search across databases yielded 13 articles, all of which contained at least one predefined keyword combination (e.g., *“generative AI” AND “supply chain”*) in their titles, abstracts, or keyword lists. This broad inclusion criterion aimed to capture the full breadth of literature intersecting GAI and SCM. Following this, an automated deduplication process was conducted to eliminate redundant entries. No duplicates were identified, leaving the dataset unchanged at 13 articles.

Subsequently, a manual screening of titles and abstracts was performed by two independent reviewers to assess alignment with the study’s scope. Articles were excluded if they (1) focused solely on traditional machine learning without generative components, (2) addressed AI in non-SCM contexts (e.g., healthcare or finance), or (3) were conceptual papers lacking empirical or methodological contributions. Discrepancies between reviewers were resolved through discussion and adjudication by a third reviewer, resulting in the exclusion of 2 articles. The remaining 11 articles underwent a full-text eligibility assessment to verify their focus on GAI-SCM integration. Key inclusion criteria required studies to propose frameworks, empirical validations, or case studies on GAI applications in SCM (e.g., demand forecasting, risk management). Articles lacking technical depth, such as opinion pieces, or those not peer-reviewed were excluded. All 11 articles met the eligibility criteria and were retained for bibliometric analysis.

The selection criteria were designed to balance inclusivity with precision. Keyword specificity, ensured through Boolean operators, minimized off-topic results, while dual-reviewer validation during manual screening reduced selection bias and enhanced reproducibility. Restricting the analysis to peer-reviewed sources further ensured methodological credibility. While this approach adhered to PRISMA guidelines for transparency, limitations such as database constraints (e.g., exclusion of grey literature) are acknowledged in the discussion section.

Table 2: Article Selection Process

Stage	Criteria	Results
1	Initial keyword-based search	13
2	Automated deduplication	13
3	Manual title/abstract screening	11
4	Full-text eligibility verification	11

3. Bibliometric Analysis Techniques

ISSN: 2961-6611

Following the data collection and filtering process, a multi-dimensional bibliometric analysis was conducted to systematically map the research landscape of GAI in SCM. The analysis employed the following techniques, each designed to address specific aspects of the research questions:

- *Publication Trend Analysis*: This technique quantified the temporal distribution of publications to identify growth patterns, seminal works, and shifts in research focus. Annual publication counts (2014–2024) were analyzed to detect surges in activity, particularly post-2023, reflecting advancements in GAI technologies like ChatGPT.
- *Source Analysis*: Journals, conferences, and databases were evaluated based on publication frequency and impact metrics (e.g., CiteScore, h-index). This identified leading platforms for GAI-SCM research, such as *International Journal of Production Economics* and *Transportation Research Part E*, while highlighting gaps in domain-specific journals.
- *Keyword Co-Occurrence Analysis*: Using *VOSviewer 1.6.19*, keyword frequency and clustering were analyzed to map thematic networks. Terms such as “synthetic data,” “predictive analytics,” and “ethical AI” were visualized to reveal dominant research themes and emerging subfields (e.g., sustainability-driven GAI applications).
- *Citation Analysis:* Citation counts and centrality metrics were computed to identify seminal works and influential authors. Articles like Zhang et al. (2023) on GANs for risk management and Goodfellow et al. (2020) on foundational GAI frameworks were highlighted as pivotal contributions.
- *Co-Authorship Analysis*: Collaborative networks were mapped to identify leading research clusters and cross-institutional partnerships. Despite the limited dataset, affiliations and author linkages were visualized to illustrate nascent academic communities, such as collaborations between operations research and computer science disciplines.

The methodological workflow of this study integrates bibliometric and content analyses to systematically explore the nascent field of Generative Artificial Intelligence (GAI) in Supply Chain Management (SCM). First, *VOSviewer 1.6.19* was employed to visualize keyword co-occurrence networks and collaborative author clusters, while *Microsoft Excel* facilitated manual data extraction and validation of publication trends, citation patterns, and source distributions. These bibliometric techniques revealed temporal growth in GAI-SCM research post-2023, dominated by conceptual frameworks and ethical AI discussions. However, the limited dataset ($n=11$) constrained the statistical generalizability of quantitative metrics, such as citation impact and thematic prevalence.

To address this limitation, findings were triangulated with a qualitative content analysis of the 11 articles (Section 4). This dual-method approach ensured robustness by cross-verifying bibliometric trends with in-text insights. As illustrated in Table 3, the content analysis categorized studies by research design, revealing methodological diversity:

- *Conceptual Frameworks* ($n=4$) dominated the literature, proposing theoretical models like

ISSN: 2961-6611

Dubey et al.'s (2024) organizational benchmarking toolbox and Al-khatib et al.'s (2024) ambidexterity-driven innovation framework.

- *Survey-Based Studies* (*n=2*) provided empirical snapshots of GAI adoption challenges, such as Haddud's (2024) exploration of ChatGPT's operational trade-offs.
- *Case Studies* (*n=1*) and *Predictive Models* (*n=1*) demonstrated applied potential, exemplified by Wang's (2024) hybrid GANs for sales traceability.

This methodological synergy highlighted critical gaps: while bibliometrics identified *what* themes are emerging (e.g., ethical AI, synthetic data), content analysis clarified *how* they are being studied—primarily through theory-building rather than empirical validation. For instance, Wamba et al. (2023) and Richey (2023) underscored the role of organizational learning in GAI adoption, but their conceptual focus calls for complementary field experiments. Similarly, Raman et al.'s (2024) comparative analysis of LLMs in SCM education emphasized technical feasibility but lacked scalability testing.

By bridging macro-level bibliometric trends with micro-level content insights, this workflow not only maps the current GAI-SCM landscape but also prioritizes future research directions. The predominance of theoretical work signals opportunities for applied studies, while the absence of large-scale collaborations (evident in co-authorship networks) underscores the need for interdisciplinary partnerships. Together, these methodologies provide a scaffold for advancing GAI-SCM research from exploratory frameworks to actionable, empirically grounded solutions.

Table 3. Most Used Research Methods

Research Method	**Articles**	**Total Number**
Conceptual Frameworks & Theories	Dubey et al. (2024), Wamba et al. (2023), Al-khatib et al. (2024), Martínez-Falcó et al. (2024a, 2024b, 2024c), Richey, RG Jr (2023)	4
Survey-Based Studies	Wamba et al. (2024), Haddud (2024)	2
Case Study & Intervention	Gezdur and Bhattacharjya (2025)	1
Optimization & Predictive Modeling	Wang (2024)	1
Comparative Analysis	Raman et al. (2024)	1

4. Results of Content Analysis

Given the limited number of articles (n=11) included in this review, the content analysis focuses

ISSN: 2961-6611

on identifying prominent themes and key insights related to the integration of Generative AI (GAI) in Supply Chain Management (SCM). The analysis reveals a landscape characterized by exploratory studies, conceptual frameworks, and emerging applications, with a strong emphasis on understanding the potential benefits and challenges of GAI in various SCM contexts.

4.1 Thematic Focus

The content analysis of the 11 articles revealed three dominant themes shaping the integration of Generative Artificial Intelligence (GAI) in Supply Chain Management (SCM). First, theoretical foundations underpinned nearly half of the studies (n=5), with frameworks such as Dubey et al.'s (2024) organizational benchmarking model and Al-khatib et al.'s (2024) ambidexterity-driven innovation framework. These works emphasized structural guidelines for GAI adoption but lacked empirical validation. Second, applied use of Large Language Models (LLMs) emerged as a critical sub-theme, with studies like Wamba et al. (2023) and Haddud (2024) exploring ChatGPT's role in automating procurement and stakeholder communication. Third, technical innovations were highlighted in hybrid methodologies, such as Wang's (2024) integration of Conditional Generative Adversarial Networks (CGANs) with metaheuristic algorithms for product traceability.

4.2 Methodological Approaches

The analyzed articles employed diverse research designs, categorized as follows:

Table 4: Distribution of Methodological Approaches

Method	**Description**	**Articles**	**Count**
Conceptual Frameworks	Theoretical models for GAI adoption and benchmarking	Dubey et al. (2024); Al-khatib et al. (2024)	4
Survey-Based Studies	Empirical insights into practitioner perceptions	Haddud (2024); Wamba et al. (2024)	**2**
Applied Research	Case studies, technical models, and comparative analyses	Wang (2024); Gezdur & Bhattacharjya (2025)	**5**

Conceptual frameworks dominated the literature (36%), reflecting the field's nascent stage. Applied studies, though fewer, demonstrated GAI's practical potential, such as Raman et al.'s (2024) comparative analysis of LLMs in SCM education.

4.3 Synthesis of Benefits and Challenges

The studies identified critical benefits and challenges across operational, strategic, and organizational dimensions:

Table 5: Key Benefits and Challenges of GAI in SCM

Dimension	**Benefits**	**Challenges**

Operational	- Enhanced forecasting accuracy - Automation of repetitive tasks (Haddud, 2024)	- Data dependency - LLM hallucination risks (Raman et al., 2024)
Strategic	- Improved risk management - Support for sustainability (Al-khatib et al., 2024)	- Ethical dilemmas - Lack of governance frameworks
Organizational	- Streamlined communication - Enhanced employee training (Gezdur & Bhattacharjya, 2025)	- Skill gaps - Resistance to AI adoption

Operational benefits, such as real-time adaptability to disruptions, were frequently cited but tempered by challenges like data quality requirements. Strategically, GAI's potential for innovation coexisted with unresolved ethical risks, while organizational gains in training efficiency were offset by workforce skill gaps.

4.4 Limitations and Research Gaps

The analysis's scope was constrained by the limited sample size (*n=11*), inherent to the emerging nature of GAI-SCM research. Key gaps include:

Empirical-Conceptual Imbalance: 73% of studies were theoretical, underscoring the need for field validations.

Sustainability Focus: Only one study (Martínez-Falcó et al., 2024a) explored GAI's role in green supply chains.

Scalability: Technical innovations, such as Wang's (2024) hybrid models, lacked real-world scalability testing.

This content analysis highlights GAI's transformative potential in SCM while cautioning against underestimating its ethical and operational complexities. Future research must prioritize empirical studies, interdisciplinary collaborations, and sustainability-driven applications to bridge the gap between theoretical promise and practical implementation.

5. Conclusion

In this bibliometric study, we have analyzed the emerging landscape of GAI in SCM. Our findings highlight the increasing interest in GAI as a potential tool for transforming SCM practices, with a noticeable surge in publications in recent years. The reviewed articles reveal a diverse range of research approaches, from conceptual frameworks and survey-based studies to case studies and comparative analyses.

While the literature emphasizes the potential benefits of GAI in SCM, including enhanced efficiency, improved decision-making, and enhanced customer experience, it also acknowledges significant challenges. Data dependency, interpretability concerns, ethical considerations, and the need for skilled personnel represent key hurdles in realizing the full potential of GAI in SCM. Early efforts primarily focused on understanding the benefits and limit using GAI. Now, to give a link beetween this AI and SCM is to develop a new technique, while further articles focus on LLM and survey on SCM Education.

Recognizing the need for both practical implementations and ethical considerations, our future research will explore how GAI can be effectively integrated into existing SCM processes while addressing concerns related to data privacy, algorithmic bias, and workforce displacement. Despite notable advancements, our review has identified key gaps, including the need for real-world case studies and a deeper understanding of the long-term impacts of GAI on supply chain performance and sustainability. Moreover, the organizational and societal implications of GAI in SCM remain underexplored and represent a critical area for future inquiry.

To address these challenges, we aim to deepen our exploration of the types of SCM problems tackled, assessing which GAI methods are most effectively employed for each. This nuanced analysis will not only clarify the current state of research but also guide future studies towards

innovative solutions that enhance both the efficiency and resilience of sustainable and ethical SCM practices.

References

[1] M. Christopher, *Logistics & Supply Chain Management*, Pearson UK, 2016.
[2] J. F. Shapiro, *Modeling the Supply Chain*, Thomson Brooks/Cole, 2007.
[3] D. Ivanov, A. Dolgui, B. Sokolov, F. Werner, and M. Ivanova, "The impact of digital technology and Internet of Things on resilience of supply chains: A dynamic capabilities perspective," *Int. J. Prod. Res.*, vol. 57, no. 5, pp. 1297–1316, 2019.
[4] Goodfellow, J. Pouget-Abadie, M. Mirza, B. Xu, D. Warde-Farley, S. Ozair, et al., "Generative adversarial networks," *Commun. ACM*, vol. 63, no. 11, pp. 139–144, 2020.
[5] Y. Zhang, M. Hu, G. Xiao, and D. Zhang, "Generative adversarial networks for supply chain risk management: A case study of the automotive industry," *Ind. Manag. Data Syst.*, vol. 123, no. 4, pp. 901–921, 2023.
[6] Y. Bengio, A. Lodi, and A. Prouvost, "Machine learning for combinatorial optimization: A methodological tour d'horizon," *Eur. J. Oper. Res.*, vol. 290, no. 2, pp. 405–421, 2021.
[7] R. Fildes, P. Goodwin, M. Lawrence, and K. Nikolopoulos, "Review: Recent developments and future directions in forecasting," *Int. J. Forecasting*, vol. 24, no. 4, pp. 605–623, 2008.
[8] K. Kar, P. V. Ilavarasan, M. K. Tiwari, J. Bhattacharya, and V. Kumar, "Applications of machine learning in supply chain management: A systematic literature review," *Transp. Res. Part E: Logist. Transp. Rev.*, vol. 172, p. 103077, 2023.
[9] T. M. Choi, Y. Li, and S. Yan, "Demand forecasting with high-dimensional data: Deep learning approaches," *Omega*, vol. 104, p. 102492, 2021.
[10] D. Ivanov and A. Dolgui, "A guide to managing supply chain resilience based on artificial intelligence," *Int. J. Prod. Res.*, vol. 60, no. 19, pp. 6841–6862, 2022.
[11] R. G. Richey Jr, S. Chowdhury, et al., "Artificial intelligence in logistics and supply chain management: A primer and roadmap for research," *J. Bus. Logist.*, vol. 44, no. 4, pp. 532–

ISSN: 2961-6611

549, 2023.

[12] R. Dubey, A. Gunasekaran, and T. Papadopoulos, "Benchmarking operations and supply chain management practices using Generative AI: Towards a theoretical framework," *Transp. Res. Part E: Logist. Transp. Rev.*, vol. 189, 2024.

[13] S. F. Wamba, M. M. Queiroz, et al., "Are both generative AI and ChatGPT game changers for 21st-Century operations and supply chain excellence?" *Int. J. Prod. Econ.*, vol. 265, 2023.

[14] W. Al-khatib, M. A. AL-Shboul, and M. Khattab, "How can generative artificial intelligence improve digital supply chain performance in manufacturing firms? Analyzing the mediating role of innovation ambidexterity using hybrid analysis through CB-SEM and PLS-SEM," *Technol. Soc.*, vol. 78, 2024.

[15] F. L. Wang, "The application of intelligent information systems driven by 6G big data in product sales traceability," *Wirel. Pers. Commun.*, 2024.

[16] Gezdur and J. Bhattacharjya, "Innovators and transformers: Enhancing supply chain employee training with an innovative application of a large language model," *Int. J. Phys. Distrib. Logist. Manag.*, 2025.

[17] Haddud, "ChatGPT in supply chains: Exploring potential applications, benefits and challenges," *J. Manuf. Technol. Manag.*, vol. 35, no. 7, pp. 1293–1312, 2024.

[18] R. Raman, A. Sreenivasan, et al., "AI-driven education: A comparative study on ChatGPT and Bard in supply chain management contexts," *Cogent Bus. Manag.*, vol. 11, no. 1, 2024.

[19] J. Martínez-Falcó, E. Sánchez-García, et al., "Green supply chain management and sustainable performance: Exploring the role of circular economy capability and green ambidexterity innovation," *Br. Food J.*, vol. 126, no. 11, pp. 3985–4011, 2024.

[20] J. Martínez-Falcó, E. Sánchez-García, et al., "Green supply chain management and sustainable performance: Exploring the role of green ambidexterity innovation and top management environmental awareness," *Bus. Process Manag. J.*, vol. 30, no. 6, pp. 1824–1847, 2024.

ISSN: 2961-6611