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Generative AI and Dynamic Capabilities for Sustainable Supply Chain Performance

Systematic Literature Review

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ABSTRACT:

Generative Artificial Intelligence (GenAI) is being adopted across global supply chains. Yet, the literature remains fragmented on how GenAI relates to dynamic capabilities development, how those capabilities translate into Triple Bottom Line (TBL) sustainability outcomes, and how this pathway operates across institutionally heterogeneous international business environments. This systematic literature review (SLR) examines how GenAI supports the development of sensing, seizing, and reconfiguring capabilities and how these capabilities relate to sustainability outcomes in international supply chains.

Peer-reviewed empirical and conceptual articles in English, published between 2020 and 2026 and addressing GenAI in supply chain, dynamic capability, or sustainability contexts, were eligible. Scopus and Web of Science were searched in March 2026 using a structured Boolean string. After PRISMA-guided screening and a six-criterion quality assessment (clear objective, theoretical grounding, methodological rigor, validity of findings, theoretical contribution, and International Business relevance), 35 studies were retained for thematic synthesis and mapped onto the Dynamic Capabilities View (DCV) and the Knowledge-Based View (KBV), organized around six application clusters, the three capability dimensions, the TBL, and a multi-level moderating context. The review was not pre-registered and received no external funding.

The review shows that the GenAI–sustainability link is indirect and capability-mediated. GenAI strengthens sensing most immediately, supports seizing where governance maturity and task-technology alignment are sufficient, and enables reconfiguring only when firms institutionalize learning across organizational boundaries. Sustainability outcomes are reached through capability-enabled practices such as green supply chain collaboration, circular economy implementation, and stakeholder co-creation, and remain unevenly developed across the TBL. Every link is conditioned by organizational, institutional, and contextual moderators, with International Business factors such as institutional heterogeneity, digital divides, and MNE coordination operating as cross-cutting boundary conditions.

The thesis offers three theoretical contributions: it extends DCV by repositioning GenAI as a generative meta-capability; integrates it with the KBV to expose the knowledge routines through which GenAI inputs become organizationally meaningful; and advances international supply chain literature by treating GenAI as a cross-border capability infrastructure conditioned by IB-specific moderators. The contributions are synthesized in an integrative conceptual framework with implications for managers, MNE executives, and policymakers.

KEYWORDS: Generative AI, Dynamic Capabilities, Sustainable Supply Chain Performance, Systematic Literature Review, Conceptual Framework, ChatGPT, Large Language Models

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1. Introduction

The business world has undergone a phenomenal transformation as a result of the emergence of Generative Artificial Intelligence (GenAI), a technology that is radically changing the way organizations operate, innovate, and generate value (Boone et al., 2025; Fosso Wamba et al., 2024; Y. Liu & Tian, 2026; Singh et al., 2026). In contrast to conventional AI, which emphasizes classification, prediction, or optimization using past trends, GenAI can produce original and complex output in the form of text, images, code, and operational strategies independently (Bahroun et al., 2026; Boone et al., 2025; Y. Liu & Tian, 2026). This generative capability helps organizations simulate alternative situations, design multi-step processes, and devise novel solutions, which is a paradigm shift in contrast to systems that only evaluate pre-existing situations but do not generate them(Boone et al., 2025; Dubey et al., 2024; Jackson et al., 2024; Lin, 2025).

The launch of ChatGPT by OpenAI in November 2022 became a watershed event that introduced GenAI capabilities to the mainstream business environment (Fosso Wamba et al., 2024; Maghroor et al., 2025). Since that time, organizations across diverse industries and geographic contexts have been exploring ways to leverage Large Language Models (LLMs) to enhance their operations and decision-making processes (Aslam et al., 2025; Bahroun et al., 2026; Fosso Wamba et al., 2024). The supply chain sector has turned into one of the most attractive fields of GenAI implementation, as it is a complex domain, and its data-driven and decision-making needs are inherent to the contemporary global supply networks involving several countries and institutional settings (Boone et al., 2025; Jackson et al., 2024; Lin et al., 2025). Leaders in the industry, such as DHL, Amazon, and Walmart, have already started to leverage GenAI tools in their global supply chain processes, claiming to have seen real increases in efficiency, agility, and service quality in their global operations (Aslam et al., 2025; Fosso Wamba et al., 2024; Maghroor et al., 2025).

At the same time, the global supply chains have been more vulnerable, interdependent, and are exposed to cross-national disruptions (Bahroun et al., 2026; Boone et al., 2025; Lin et al., 2025). These vulnerabilities were brought into sharp focus by the COVID-19 pandemic, which showed the vulnerability of internationally spread supply chains and the need to find more resilient and dynamic ways of conducting operations in a variety of institutional settings (Riad et al., 2024; Singh et al., 2026; Sodhi & Tang, 2021).

Modern supply chains have to contend with issues related to demand variability, supplier risks, geopolitical tensions, trade policy shifts, and climate-related shocks, all of which vary greatly across regional regulatory frameworks (Bahroun et al., 2026; Boone et al., 2025; Lin et al., 2025). These facts have made technologies that can improve organizational capabilities of sensing, responding to, and recovering from disruptions across the cross-border environments to be of strategic significance (Bag et al., 2025; Bahroun et al., 2026; W. Liu et al., 2026; Riad et al., 2024).

Meanwhile, sustainability has transformed from a marginal issue to a core strategic principle of supply chain management (Khan et al., 2021; Naz et al., 2022; Stroumpoulis & Kopanaki, 2022). The stakeholders are becoming more insistent that organizations should show their environmental responsibility, social responsibility, and economic sustainability throughout their supply networks (Agyabeng-Mensah et al., 2024; Govindan et al., 2013; Naz et al., 2022; Seuring & Müller, 2008). Sustainable supply chain management (SSCM) has evolved to embrace the Triple Bottom Line (TBL) approach, demanding that organizations balance environmental stewardship, social equity, and economic viability while navigating diverse regulatory pressures from the European Union, Asia, and North America (Ahi & Searcy, 2015; Bhattacharya et al., 2024; Govindan et al., 2013; Seuring & Müller, 2008). The varying ESG disclosure requirements, climate regulations, and sustainability reporting frameworks across jurisdictions create additional complexity for multinational enterprises (MNEs) seeking to achieve sustainable supply chain performance (Bag et al., 2026; Bahroun et al., 2026).

1.1 The International Business Perspective of This Study

This study is firmly grounded in the International Business (IB) discipline, examining how GenAI-enabled capabilities and sustainable supply chain performance operate within distinctly international contexts. Several interconnected factors establish the IB relevance of this research.

Contemporary supply chains are global, including various countries, institutional settings, and cultures (Dubey et al., 2024; Lin et al., 2025; Zahra et al., 2022). The logistics of material, information, and capital flows in these different environments introduce distinctive challenges, such as differences in digital infrastructure, technological preparedness, and workforce capacity, which cannot be met by domestic supply chain analysis (Bahroun et al., 2026; Lin et al., 2025; Qiao & Zhao, 2025). Bag et al. (2025) further emphasize that GenAI-enabled supply chain practices do not yield the same results in India and South Africa due to the polycrisis experience and varied institutional settings.

At the same time, cross-border knowledge flows, international competition, and global uncertainty act as key drivers of dynamic capabilities (Etemad, 2022; Teece, 2007, 2025; Zahra et al., 2022). In this context, sensing and seizing, and reconfiguring capabilities that organizations build based on the integration of GenAI, should consider the information asymmetry across geographical markets, differences in technological adoption between different cultures, and the degree of digital maturity within the subsidiary operations (Bag et al., 2025; Dubey et al., 2024; Jackson et al., 2024; Lin et al., 2025). These factors highlight that capability development is shaped by international complexity rather than being universally transferable.

Moreover, the jurisdiction level of demands towards sustainability is very different, with diverse regulatory pressures (Bag et al., 2026; Bhattacharya et al., 2024; Dubey et al., 2024). The EU ESG disclosure and circular economy rules are significantly different in Asia and North America, which poses a challenge to compliance among MNEs, and long-term ESG planning is specifically challenging due to the lack of uniform cross-jurisdictional standards (Bag et al., 2026; Bhattacharya et al., 2024). GenAI can be used to provide potential solutions by synthesizing heterogeneous and multi-jurisdictional sustainability data and overlaying it onto supplier networks to assist with the dynamic risk registers (Bahroun et al., 2026).

However, MNEs have their own issues with the development and implementation of GenAI capabilities in their international operations (Bahroun et al., 2026; Li et al., 2024; Lin et al., 2025). The tendency towards the centralization of adoption in digitized, data-rich spaces, as well as the underrepresentation of SMEs and less resourceful regions, is an indicator that there is a risk of increasing digital inequalities with far-reaching effects on international competitiveness (Bahroun et al., 2026; Maghroor et al., 2025).

By addressing these IB-related aspects, the review helps realize how GenAI can support dynamic capabilities that can improve sustainable supply chain operations in various global settings, reflecting the institutional heterogeneity and cross-border coordination issues that make IB research unique in the view of domestic operations management.

1.2 Research Problem and Gap

Although the literature on GenAI applications in supply chain management has expanded rapidly, critical gaps persist that limit both theoretical understanding and practical guidance for organizations seeking to leverage GenAI for sustainable supply chain outcomes in international business contexts.

The first and most significant gap relates to the limited application of the dynamic capabilities perspective to GenAI-driven sustainability in global supply chains. Although sensing, seizing, and reconfiguring capabilities offer a rigorous theoretical foundation for analyzing organizational adaptation, their application to GenAI remains nascent. Kurrahman et al. (2025) offer a structured effort to integrate DCV with organizational learning theory for green supply chain management, yet acknowledge that the pathways linking GenAI-enabled data processing to operational reconfiguration remain insufficiently conceptualized. Liu and Tian (2026) also discovered that the processes through which generative models increase various dimensions of distinct capabilities, and how they can be converted into sustainable supply chain performance, are not systematically explored in the context of systems involving multiple stakeholders and cross-cycle knowledge flow.

The second gap relates to the theoretical processes through which GenAI adoption translates into sustainability outcomes. Bahroun et al. (2026), in their systematic review of 98 studies, find that while nearly four-fifths of GenAI applications are concentrated in Plan and Enable functions, empirical evidence remains largely confined to prototypes and rarely tracks system-wide Key Performance Indicators (KPIs). Kurrahman et al. (2025) reinforce this observation by noting that studies focus heavily on reconfiguration while neglecting the data acquisition prerequisites for sustainable value generation, thereby leaving the capability-building mechanisms between adoption and sustainability outcomes under-theorized.

A third deficiency relates to multi-dimensional obstacles to GenAI in international supply chains. Maghroor et al. (2025) demonstrate that human-related issues such as employee resistance, skill shortages, and ethical issues are major hindrances and aggravated by data integrity. Fosso Wamba et al. (2024) also conclude that the most common challenges expressed by supply chain professionals are the accuracy of the data, its confidentiality, and the reliability of technology. Although this is acknowledged, Bahroun et al. (2026) observe that the literature does not provide governance models that specify how corporations must monitor data provenance, impose operational limitations, and demand human approval, an absence that is particularly pronounced when it comes to MNEs, where the barriers of implementation and compliance requirements are heterogeneous among subsidiaries functioning under varying institutional settings.

The last gap relates to fragmented theoretical integration. GenAI, dynamic capabilities, and sustainable supply chain performance are mostly discussed in the literature as separate constructs but not as parts of a single framework. Li et al. (2024) specifically requests studies that can help to understand the mediating variables and boundary conditions of the GenAI-sustainability relationship. Multi-theoretic efforts, including Bag et al. (2025), integrating ethical theory, DCV, and conservation of resources theory, are confined to the country-specific context, and a gap exists in frameworks that can respond to cross-border complexity and MNE-specific issues. Further, the complexity of international regulation and international institutions has not been adequately theorized.

Previous studies indicate that ESG regulations are often ambiguous, and companies have to cope with conflicting disclosure requirements (Bag et al., 2026). The transnational application of GenAI also introduces information security, data transfer, and legal harmonization issues that, as well as the ever-changing sustainability reporting requirements, make the long-term ESG planning across the regions unpredictable (Bahroun et al., 2026; Bag et al., 2026).

1.3 Research Objectives

Given the research gaps identified above, this systematic literature review (SLR) aims to develop a coherent understanding of how GenAI contributes to the development of dynamic capabilities that enable sustainable supply chain performance in international business contexts. The overarching research objective guiding this study is:

To systematically analyze how GenAI enables the development of dynamic capabilities (sensing, seizing, and reconfiguring) for sustainable supply chain performance across diverse international business contexts.

1.4 Research Questions

This SLR addresses the following main research question:

How does GenAI contribute to the development of dynamic capabilities that enable sustainable supply chain performance in international business contexts?

To answer this overarching question, the study pursues three specific sub-questions:

RQ1: What does the existing literature say about GenAI applications in sustainable supply chain management?

RQ2: How do GenAI technologies support the development of sensing, seizing, and re-configuring capabilities?

RQ3: How do these dynamic capabilities translate into improved sustainability outcomes within international supply chains?

1.5 Scope and delimitations of the study

This is a SLR on peer-reviewed scholarly articles investigating the use of GenAI in supply chain management with a clear emphasis on sustainability benefits and organizational capacities. The timeframe covers the period between 2020 and 2026, which is when modern GenAI technologies have appeared and evolved at a rapid pace, as the transformer-based models were released.

The review covers the studies carried out on the use of different GenAI technologies, such as Large Language Models (LLMs) like GPT and BERT variants, conversational AI systems like ChatGPT, Generative Adversarial Networks (GANs), variational autoencoders (VAEs), and agentic AI in the supply chain. Research that only uses traditional machine learning or only uses a limited application of AI without generative aspects is not included in the core analysis but can be used as a theoretical background.

The review is not geographically restricted, but it recognizes that the majority of the empirical research is based on developed economies and large emerging markets like China and India. This level of concentration can be a constraint to the applicability of the findings to other settings. Also, GenAI technologies are rapidly changing, so new developments can be introduced that are beyond the scope of this review.

2. Theoretical Background

This chapter builds the theoretical framework of the study by bringing together three streams of literature -GenAI, the Dynamic Capabilities View (DCV), and Sustainable Supply Chain Management (SSCM) to provide a united framework. The chapter considers these areas not as isolated, but as interconnected perspectives that can be used to understand how GenAI supports the development of organizational capabilities for sustainability in international supply chains. Section 2.1 defines GenAI in terms of its strategic and managerial implications for international supply chain management. Section 2.2 provides an overview of the main theoretical perspective on capability development. Section 2.3 introduces the outcome perspective of SSCM and its TBL approach.

2.1 Generative Artificial Intelligence (GenAI)

GenAI represents a qualitative change to the way organizations can apply AI systems. GenAI is not focused on classifying, predicting, or optimizing its results based on the patterns in historical data and, unlike traditional AI, learns the underlying structure of the inputs in its training, thus generating new, contextually relevant outputs: text, simulations, synthetic data, strategic choices, and operational plans (Feuerriegel et al., 2024; Mariani & Dwivedi, 2024). This generative ability allows organizations to go beyond analysis. It allows them to simulate futures, design alternatives, and synthesize knowledge based on heterogeneous sources in ways that were infeasible before (Bahroun et al., 2026; Boone et al., 2025). For International Business, GenAI's strategic relevance lies primarily in three interconnected organizational functions:

First, it augments information processing ability: Global supply chains operate with diverse, multi-lingual, multi-channel data across geographical and institutional settings, and GenAI systems, particularly Large Language Models (LLMs) coupled with Retrieval-Augmented Generation (RAG), can process these inputs at a scale and speed that is impossible for humans to achieve (Dubey et al., 2024; Lin et al., 2025).

Second, it enhances managerial cognition: GenAI provides scenario analyses, trade-off simulations, and contingency options for responding to disruptions, thus increasing the choice set of managers operating under uncertainty in a cross-border environment (Jackson et al., 2024; Boone et al., 2025).

Third, it facilitates cross-border coordination: For MNEs coordinating their supplier networks, compliance requirements, and logistics across diverse institutional environments, GenAI offers a shared analytical platform that can integrate institutionally diverse information (Bahroun et al., 2026; Maghroor et al., 2025).

Use cases of GenAI in supply chain span the entire Supply Chain Operations Reference (SCOR) model (Plan, Source, Make, Deliver, Return, Enable). However, the evidence to date indicates a focus on Plan and Enable, with less attention given to Make, Return, and cross-border coordination (Bahroun et al., 2026). The GenAI application domains include demand forecasting, supplier management, risk surveillance, process optimization, logistics, and sustainability analytics. For the theoretical purposes of this chapter, the key conceptual point is that GenAI operates most powerfully not as a standalone automation tool but as an organizational enabler that amplifies existing capabilities and, under the right governance conditions, helps build new ones. This capability-enabling framing is theoretically significant. Liu and Tian (2026) conceptualize GenAI as a generative capability, a higher-order organizational process rooted in knowledge acquisition, integration, and continuous updating. Bag et al. (2025) similarly position GenAI as a second-order dynamic capability that shapes how first-order capabilities are developed and applied. This positions GenAI not as an exogenous technological input but as a meta-level organizational capacity whose value is expressed through the sensing, seizing, and reconfiguring capabilities it enables. Critically, this meta-capability framing also explains why GenAI's organizational benefits are not automatic; instead, they depend on the governance infrastructure, absorptive capacity, and collaborative routines that firms put in place to translate AI-generated insights into organizational action(Kurrahman et al., 2025; Li et al., 2024).

2.2 Dynamic Capabilities View (DCV)

Dynamic capabilities refer to the capability of the firm to combine, create, and reorganize both internal and external capabilities in reaction to changes in the environment (Teece et al., 1997). Later, it was theorized that capabilities involve organizational processes such as decision-making and coordination routines, which facilitate resource transformation and strategic renewal (Eisenhardt & Martin, 2000). Teece (2007) further elaborates on this point of view and outlines three fundamental dimensions of sensing, seizing, and reconfiguring as the dimensions that offer a systematic approach to the study of how firms develop the opportunity, respond strategically, and reorganize operations.

Dynamic capabilities are a hierarchical and interdependent set of three dimensions (Teece, 2007). Sensing capabilities relate to the process of scanning, searching, and exploring opportunities and threats in technologies, markets, and competitive environments (Teece et al., 1997). This demands a commitment to the research, intelligence in the market, and outside of the company collaborations to identify weak signals and forthcoming trends (Le & Behl, 2024). Seizing capabilities entails marshaling resources to respond to opportunities and value capture by new products, processes, or business models (Teece, 2007). This necessitates decision-making structures, resource allocation mechanisms, and organizational agility to respond to perceived opportunities (Kurrahman et al., 2025). Reconfiguring capabilities refers to continual change and renewal of resources, structures, and routines to ensure evolutionary fitness (Teece et al., 1997). This necessitates adaptability, integration of knowledge, and coordination of both internal and external resources(McDougall et al., 2022).

The micro foundations of dynamic capabilities, the distinct skills, processes, organizational structures, decision rules, and managerial cognition patterns that underpin sensing, seizing, and reconfiguring are shaped by organizational history and learning (Teece, 2007). Such micro foundations are becoming more mediated by information technologies, data analytics, and artificial intelligence systems in the digital era (Le & Behl, 2024; Yang et al., 2024). The advent of GenAI technologies could be a paradigm shift in the development and implementation of dynamic capabilities within organizations, but this connection has not been theorized (Kurrahman et al., 2025).

2.3 Sustainable Supply Chain Management (SCCM)

SCCM has transformed from a marginal issue to a strategic priority in contemporary organizations (Khan et al., 2021; Stroumpoulis & Kopanaki, 2022). According to Seuring and Müller (2008), SSCM is the administration of material, information, and capital flows, and inter-firm cooperation with the express focus on all three dimensions of sustainable development, including environmental, social, and economic. This TBL orientation is in which organizations balance conflicting imperatives of performance simultaneously, and not optimize performance on any single line in isolation from the others (Ahi & Searcy, 2015; Govindan et al., 2013).

The environmental dimension encompasses the usage of resources, emissions, wastes, and the general ecological footprint of the operations of the supply chain. Some of the key performance indicators include carbon footprint, energy efficiency, water consumption, material recovery rates, and biodiversity impact. Regulatory forces, in particular climate disclosure regulations, the EU circular economy regulations, and the construction of carbon pricing systems, have increased the environmental performance, which was a voluntary commitment before a compliance obligation with direct financial consequences of non-compliance (Bhattacharya et al., 2024; Bag et al., 2026).

The social aspect deals with human wellbeing across the supply chain, including labor standards, health and safety, community relations, human rights, diversity and inclusion, and fair wage practices. Social performance has become a material business risk, especially among MNEs with large supplier bases in various regulatory structures, due to stakeholder activism, mandatory human rights due diligence policies in many jurisdictions, and increased investor attention towards ESG profiles (Naz et al., 2022; Agyabeng-Mensah et al., 2024).

The economic aspect encompasses the operational and financial performance, cost efficiency, profitability, quality, delivery performance, and customer satisfaction; however, it draws the line between long-term economic sustainability and profit maximization in the short term. At the core of this difference lies stakeholder balancing and maintaining the productive capacity of the firm across time, which directly connects economic sustainability with the dynamic capabilities required to respond to the changing market and regulatory environments (Seuring & Müller, 2008).

3. Research Methodology

This chapter presents the SLR methodology employed to address the research questions. The methodology follows PRISMA 2020 guidelines (Page et al., 2021) to ensure rigor, transparency, and replicability.

3.1 Research Design

In this study, the SLR methodology is the most suitable approach to this research because of a number of reasons. To start with, the area is still developing fast, and there are quite a number of new publications that need to be synthesized systematically so that the boundaries of the up-to-date knowledge can be determined. Second, various theoretical insights should be combined to construct a holistic view of dynamic capabilities supported by GenAI. Third, a conceptual framework is developed based on evidence-based identification of research gaps to conduct research in the future.

The SLR methodology adheres to a three-step regimen suggested by Tranfield, Denyer, and Smart (2003). The SLR approach adheres to the three steps: planning the review, conducting the review, and reporting and disseminating the findings (Tranfield et al., 2003). The use of PRISMA 2020 guidelines is required to have a clear and complete reporting of the review process (Page et al., 2021).

3.2 Search Strategy

To find the literature on GenAI, sustainable supply chain management, and dynamic capabilities, a structured keyword strategy was adopted in the search of Scopus and Web of Science Core Collection. The search was in the TITLE-ABS-KEY field in Scopus, which is a search of titles, abstracts, and keywords. The search was done in the Web of Science using the Web of Science Core Collection Topic field, which is a field that contains the title, abstract, author keywords, and Keywords Plus. A combination of three sets of terms in the form of the Boolean operator AND was used, with one set of terms representing generative AI, a set of terms representing situations of sustainable supply chain and logistics, and a set of terms representing dynamic capabilities. Synonyms and related expressions within each group were joined with OR, and truncation was employed as a means of capturing lexical variants. The Scopus search string was defined as:

TITLE-ABS-KEY (("Generative AI" OR "GenAI" OR "LLM" OR "Large Language Model*" OR "ChatGPT") AND ("Sustainable supply chain performance" OR "supply chain*" OR "logistics" OR "sustainab*" OR "green" OR "ESG") AND ("dynamic capabilit*" OR "sensing" OR "seizing" OR "reconfigur*")).*

The same conceptual search structure was then adapted to the syntax requirements of Web of Science Core Collection. The literature search was conducted on 21 March 2026.

3.3 Inclusion and Exclusion Criteria

Table 1 presents the inclusion and exclusion criteria applied during the screening process.

Code	**Inclusion Criteria**	**Exclusion Criteria**
IC1/EC1	Focuses explicitly on GenAI technologies	Studies addressing only traditional ML/AI without generative components
IC2/EC2	Addresses the supply chain management context	Non-supply chain contexts (e.g., pure marketing, HR)
IC3/EC3	Incorporates sustainability, dynamic capabilities, or performance outcomes	Purely technical AI papers without management focus
IC4/EC4	Empirical study, conceptual framework, or systematic review	Opinion pieces, editorials without framework or evidence
IC5/EC5	Published in English	Non-English publications
IC6/EC6	Peer-reviewed journal article	Conference papers, working papers, dissertations, books

Table 1. Inclusion and Exclusion Criteria

3.4 PRISMA Framework

The PRISMA flow diagram (Figure 1) summarizes the identification, screening, eligibility, and inclusion stages of the review process. The initial database search yielded 218 and 215 records in Scopus and Web of Science, respectively. After that, the search results were filtered by subject area “Business, Management and Accounting”, “Economics, Econometrics and Finance”, and “Decision Science” in Scopus and “Business Economics”, “Operations Research and Management Science”, and “Transportation” in Web of Science. Only articles published in the English language, published between 2020 and 2026, were selected for study. In total, 74 articles were selected for further screening. After removing 10 duplicates, 64 articles went through title and abstract screening. Of these, 20 were excluded as not meeting the inclusion criteria, leaving 44 articles for full-text assessment. After the detailed evaluation, 35 articles were included in the final synthesis.

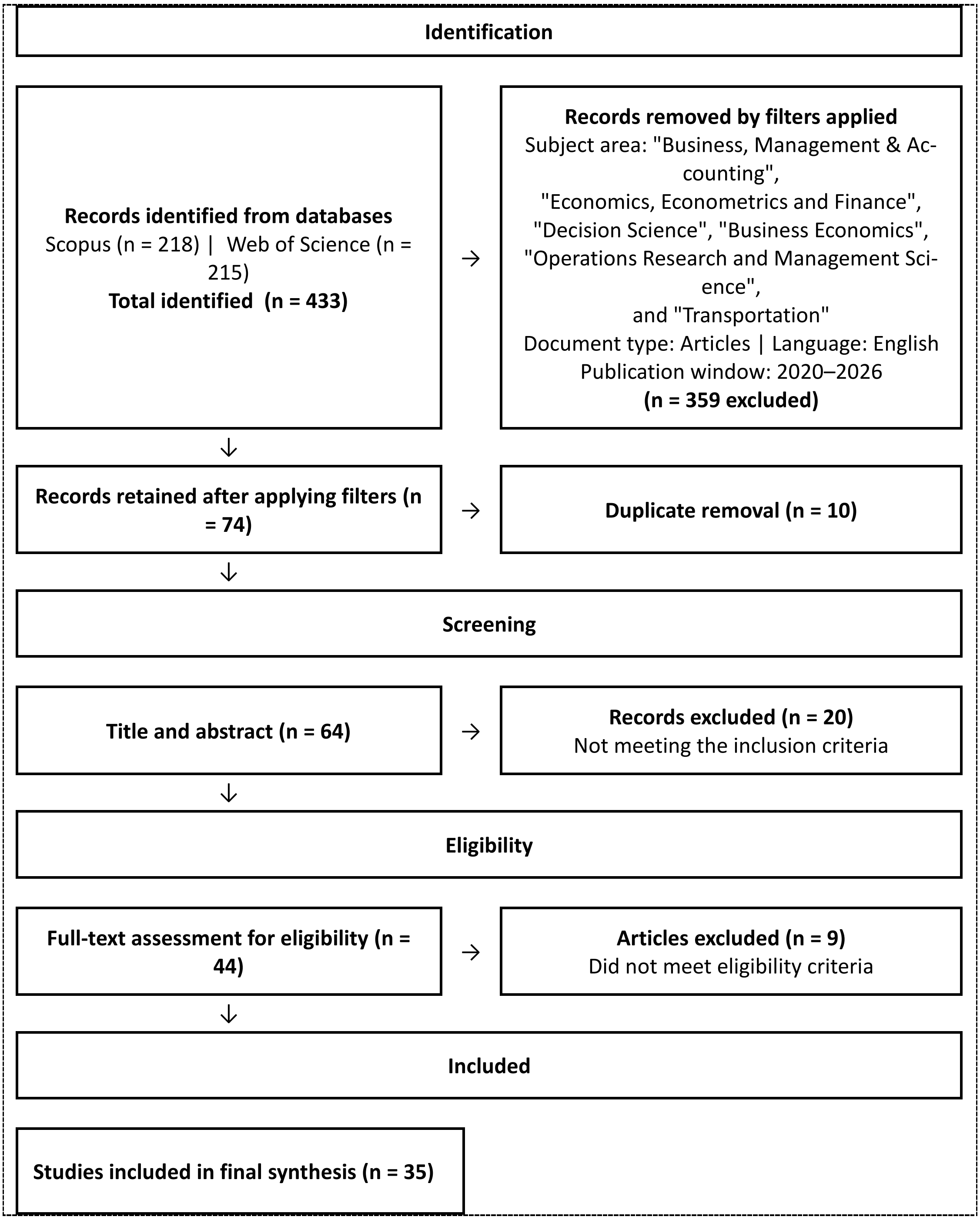

Figure 1. PRISMA Flowchart (Page et al., 2021)

3.5 Quality Assessment

Each included study was assessed using a six-criterion quality framework scored on a 0-3 scale, yielding a maximum score of 18 points. Table 2 presents the quality assessment criteria.

Criterion	Description	Scale
Q1: Clear Objectives	Research questions clearly stated, specific, achievable; methodology aligned	0-3
Q2:Theoretical Grounding	Strong theoretical framework (DCV, OIPT, RBV, PBV); well-justified; extends theory	0-3
Q3: Methodology Rigor	Appropriate method; well-documented; replicable; robust analysis	0-3
Q4: Validity of Findings	Findings well-supported by evidence; limitations acknowledged	0-3
Q5: Contribution	Significant theoretical and/or practical contribution	0-3
Q6: IB Relevance	International/cross-border focus; MNE context; global implications	0-3

Table 2. Quality Assessment Criteria

Quality Thresholds: High Quality (≥16 points): Include with high confidence. Medium Quality (12-15 points): Include with caution, noting limitations. Low Quality (<12 points): Exclude unless addressing critical gaps with justification. The score Metrix of the quality assessment is available in Appendix 2.

3.6 Data Extraction and Synthesis

A structured extraction form captured key information from each study including bibliographic details, research objectives, theoretical framework, methodology, sample characteristics (country, industry, and sample size), Dynamic capability dimensions addressed (sensing/seizing/reconfiguring) in relation to GenAI, sustainability dimensions (environmental/social/economic) in relation to GenAI, GenAI technology examined, key findings, limitations and Future research directions. related to capabilities and/or sustainability, and limitations. Appendix 1 presents the data extraction from the corpus of the SLR.

Data synthesis employed thematic analysis, organizing findings according to the three search questions. For each research question, themes were identified inductively from the literature and organized into higher-order categories. This approach enabled systematic synthesis while maintaining sensitivity to the diverse conceptualizations and findings across studies.

3.7 Limitations of Methodology

The systematic review approach has several limitations that need to be taken into account. For one thing, the study is limited to only two databases and English literature. This could mean that any other valuable research that may exist in other languages or other databases is excluded from consideration. Additionally, GenAI systems are rapidly advancing, meaning not everything new might yet appear in scholarly journals. Third, the emphasis on peer-reviewed materials leaves out the potentially useful information on industry practice and grey literature. Fourth, the synthesis will be dependent on the quality and completeness of reporting in the papers; non-consistent or incomplete reporting can be a limiting factor of the synthesis. Lastly, thematic analysis is an interpretive approach that risks introducing bias in the researcher, though this was addressed by systematic steps and clear writing.

4. Findings

This chapter presents the findings of the SLR, organized to directly address the three research sub-questions. Section 4.1 offers a descriptive overview of the reviewed literature. Sections 4.2–4.3 address RQ1 and RQ2 by examining GenAI applications in sustainable supply chain management and their role in developing dynamic capabilities. Section 4.4 addresses RQ3 by tracing how those capabilities translate into sustainability outcomes. Section 4.5 documents the moderating and contingency factors that condition these relationships.

4.1 Descriptive Analysis

4.1.1 Publication Trends

The 35 articles included in this systematic review demonstrate a rapidly evolving research domain. The frequency of publication rose markedly between 2023 and 2026, which is indicative of a rise in academic interest in GenAI applications due to the release of ChatGPT in November 2022. Most of the articles were written in 2024-2026, which means that it is a new area with a rapidly developing academic interest. Prominent journals in the sample were high-impact journals such as International Journal of Production Economics, Transportation Research Part e-logistics, Transportation Review, Business Strategy and the Environment, and Technological Forecasting and Social Change. Figure 2 shows the trend of the publication. It shows the sharp rise in publications in 2025.

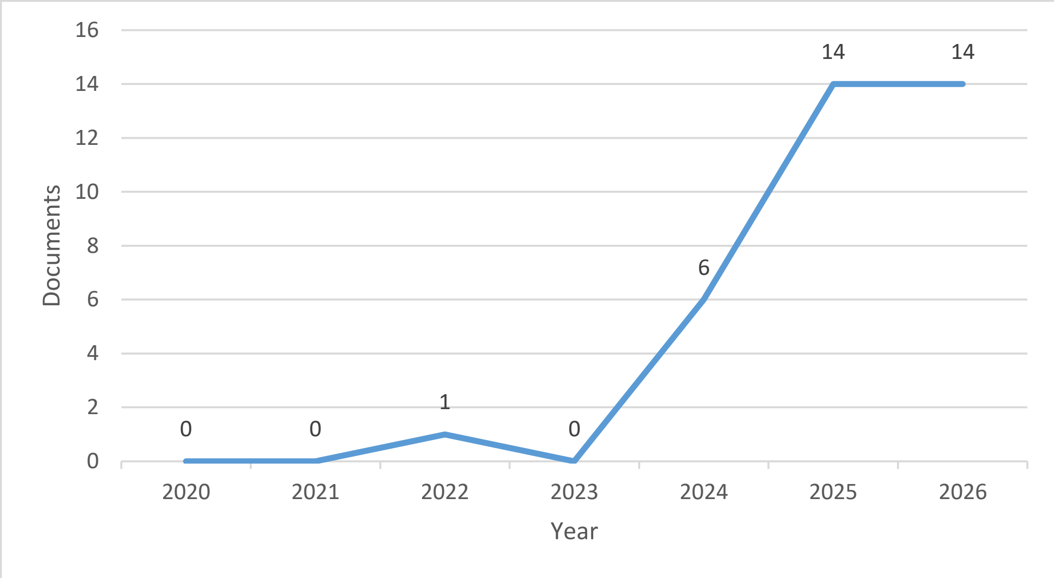

Figure 2: Publication Trends

4.1.2 Methodological Distribution

The reviewed articles employed diverse research methodologies. Methodological descriptions for 30 of the 35 selected articles are presented, while the remaining five lack distinct methodology sections or being solely bibliographical studies. Among the 30 articles, the Quantitative empirical studies utilizing survey-based approaches predominated (n=19), with Partial Least Squares Structural Equation Modeling (PLS-SEM) and Covariance-Based SEM being the most common analytical techniques. Qualitative studies, including case studies and interview-based research, comprised a smaller proportion (n=4), typically exploring emerging phenomena or building theoretical frameworks. Mixed methods design (n=4) combined quantitative surveys with qualitative insights. SLR papers (n=3) provided theoretical frameworks and research agendas. Figure 3. shows the methodologies applied in the reviewed articles.

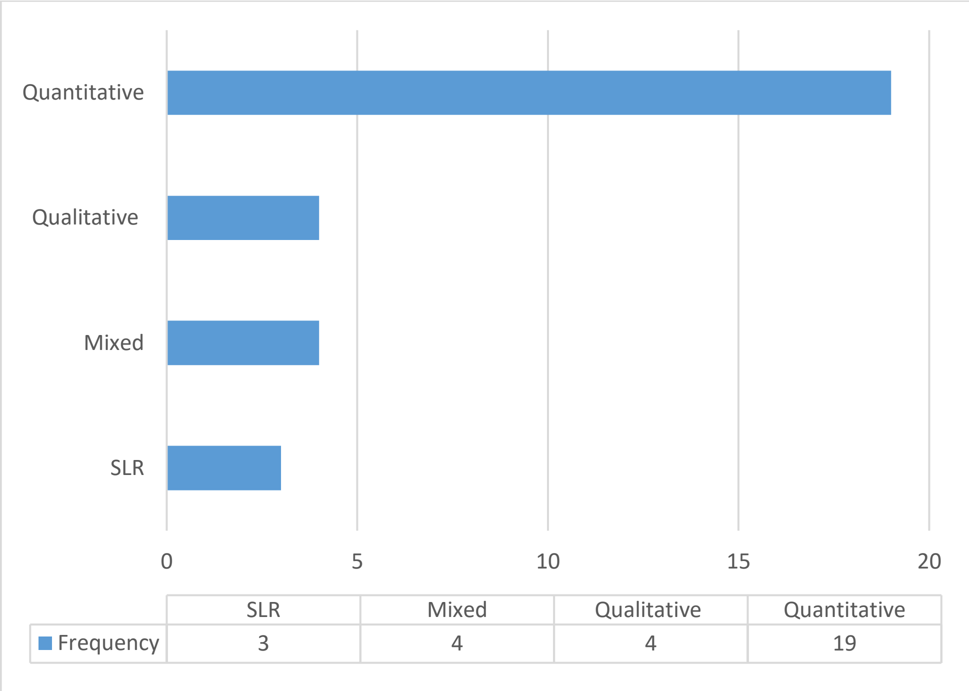

Figure 3. Research Methods

4.1.3 Geographic Distribution

The empirical evidence base comprises 22 articles within the corpus of the SLR, which exhibits high levels of concentration in Asia, especially in China (n = 7) and India (n = 4). This can be explained by the fact that these are emerging economies in terms of digitalization and the implementation of artificial intelligence. Other Asian countries (n = 2) also make their contributions to the area, which supports the leading role of Asia in the sphere. Other limited yet valuable regional insights are found in studies carried out in Europe (n = 2) and North America (n = 2). Moreover, it is possible to point to a significant proportion of multi-country or global studies (n = 5) that show increasing interest in creating generalized and transferable knowledge in various settings. Comprehensively, the results presented in Figure 4. show that there is a geographical disproportion of literature that is clearly biased towards the emerging Asian economies, and the developed regions are relatively underrepresented.

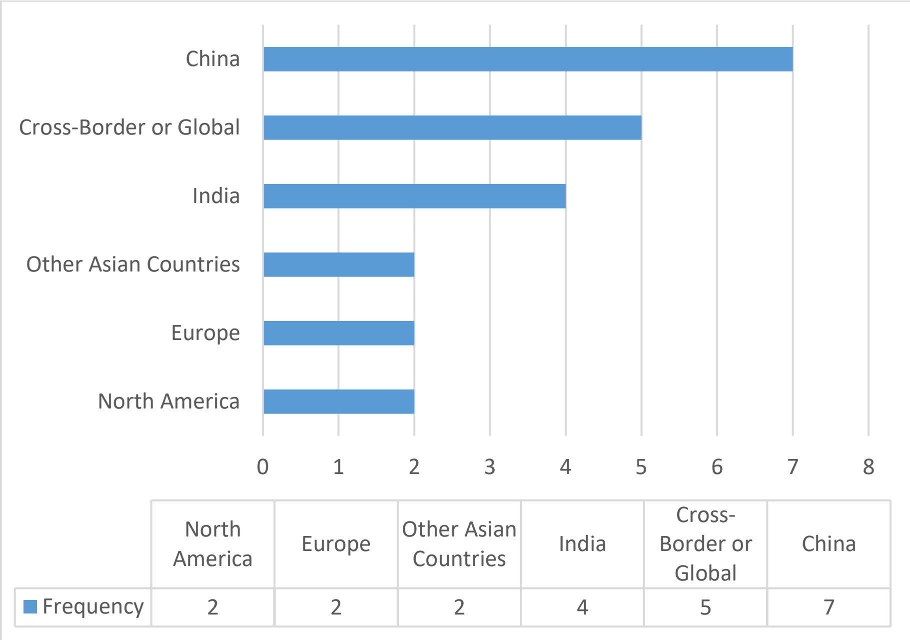

Figure 4. Geographical Distribution

4.1.4 Industry context

The reviewed literature encompasses diverse industry contexts, including manufacturing, retail, logistics, automotive, and technology, with a pronounced strategic focus on manufacturing supply chains navigating sustainability pressures and circular economy transitions. The methodological approach of quantitative studies included in this systematic review demonstrates a bifurcated method to the collection of data that captures both micro-level organizational dynamics and macro-level performance outcomes. Primary survey-based research focused mainly on mid-senior-level supply chain managers, operations executives, and technology professionals, with sample sizes of between 213 and 2,000 respondents. Parallel to that, quantitative macro-level studies of firm sustainability and resilience were based on large secondary panel datasets and algorithmic text-mining corpora, comprising between 1,448 and more than 40,000 observations.

4.2 GenAI Applications in Sustainable Supply Chain Management

4.2.1 Categories of GenAI Applications

Across the 35 reviewed literature, the most developed area of application for GenAI is demand forecasting and predictive planning (Bahroun et al., 2026; Boone et al., 2025). (Boone et al., 2025; Riad et al., 2024). GenAI combines unstructured data, including social media feeds, news, macroeconomic indicators, and historical data to enhance predictive power over traditional time-series models (Boone et al., 2025; Riad et al., 2024). Models based on transformers have been shown to improve correlation of forecasts with actual demand, and are especially beneficial in volatile, multi-market settings where qualitative signals have strategic value (Bahroun et al., 2026; Jackson et al., 2024).

The reviewed literature shows that supplier management and risk surveillance are closely related application domains. LLMs equipped with retrieval augmented generation (RAG) are deployed to autonomously mine ESG disclosures, compliance certification, and internet content to create structured supplier risk data that combines financial, sustainability, and regulatory information (Bahroun et al., 2026; Sonar et al., 2026). At the same time, their study finds that GenAI tracks open-source news and geopolitical updates to identify early warning signs and create disruption scenarios with real-time mitigation suggestions (Riad et al., 2024; Guo et al., 2026).

The reviewed literature further highlights that the deployment of generative digital twins and synthetic data is used to optimize processes, production, and inventory management by testing the operational policies under stress in unobserved situations (Boone et al., 2025). More sophisticated architectures, such as Variational Autoencoders (VAEs), GANs, and transformer models, are used to create realistic future demand patterns and extreme cases of disruption, which allow adjusting safety stock dynamically and testing inventory policy (Bahroun et al., 2026; Necula and Rieder, 2025). Within the production domain, GenAI is used to simulate manufacturing schedules and equipment failure modes, which can be used for predictive maintenance and optimize resource allocation before actual implementation (Sonar et al., 2026). Likewise, in Logistics and distribution, GenAI applications integrate real-time satellite imagery, GPS telemetry, and weather data to determine adaptive routing options (Boone et al., 2025). Unlike fixed planning models, GenAI proactively reroutes shipments across all means of transport, simultaneously optimizing cost, delivery speed, and carbon footprint (Boone et al., 2025; Riad et al., 2024).

Across the reviewed studies, the six application clusters share two reported features. Heterogeneous data sources are integrated into structured operational outputs, and reported deployments concentrate in the Plan and Enable functions of the SCOR model (Boone et al., 2025; Sonar et al., 2026; Bahroun et al., 2026). The literature does not yet provide system-level KPIs across these clusters.

4.2.2 Sustainability-Specific Applications

Apart from operational efficiency, the reviewed literature identifies several GenAI application segments that directly contribute to sustainability outcomes, converting environmental compliance from a reporting requirement into an active operational capability. In sustainable sourcing and ESG risk assessment, NLP and RAG techniques enable autonomous mining of supplier sustainability disclosures to generate structured ESG risk profiles, identify low-carbon sourcing alternatives, and automate sustainability audits (Bahroun et al., 2026; Sonar et al., 2026). The latter are especially useful to MNEs that must cope with divergent ESG reporting frameworks across jurisdictions, e.g., EU taxonomy requirements, which require data granularity at an upstream level, which GenAI can facilitate by synthesizing heterogeneous multi-language supplier networks. GenAI also accelerates Life Cycle Assessment (LCA) by extracting carbon and energy data from upstream disclosures and simulating emissions-aware routing and warehouse packing to minimize material waste (Bahroun et al., 2026; Wu et al., 2024).

The reviewed literature further identifies that generative models used in the transition to a circular economy and in eco-design are used to simulate reverse logistics and material recovery rates, and safe operation of high-risk processes, including battery recycling, to aid the transition to closed-loop processes. Lukács et al. (2026) document a generative eco-design intelligence, which is capable of modeling environmental trade-offs, the simulation of regenerative product-service systems, and the assurance of compliance with emerging regulations of the circular economy through the LLM-supported parsing of regulations. On the facility and network level, it can be integrated with digital twins and smart decision systems, allowing real-time optimization of energy use and monitoring of emissions to facilitate the continuous redesign of the processes in response to changing environmental policies and consumer sustainability expectations (Qin & Zhang, 2026; Wu et al., 2024). In all these domains, the literature warns that GenAI outputs need to be based on proven environmental data to prevent greenwashing or false optimization of efficiency (Bag et al., 2026).

4.2.3 Integration Challenges

The reviewed literature reports three types of barriers that consistently dominate the literature and moderate the sustainability impact of GenAI through supply chains as well. The most commonly mentioned operational barriers include data-related issues, such as accuracy, provenance, and confidentiality, especially when ESG data quality differs between or among geographies or supplier levels (Fosso Wamba et al., 2024; Maghroor et al., 2025). Human and organizational barriers involve skills deficiencies, staff resistance, and a lack of governance structures that outline how companies are expected to track data integrity, impose operational limits, and demand human supervision - obstacles that are compounded by MNEs that coordinate across subsidiaries that operate in different institutional settings (Bahroun et al., 2026; Maghroor et al., 2025). The presence of conflicting AI governance standards and non-harmonized sustainability reporting frameworks leads to ethical and regulatory issues, posing uncertainty of compliance, long-term planning challenges to firms operating in multiple jurisdictions (Bag et al., 2026; Bahroun et al., 2026).

4.3 GenAI and Dynamic Capabilities Development

4.3.1 GenAI for Sensing Capabilities

Across the reviewed literature, GenAI emerges consistently as an advanced sensing mechanism, enabling firms to detect risks, environmental stressors, and operational anomalies at a speed and scale that conventional digital tools cannot match. This capacity operates through large-scale processing of heterogeneous, unstructured data, operational signals, sustainability indicators, supplier disclosures, and external environmental inputs that fragmented systems cannot integrate efficiently (Kurrahman et al., 2025; Liu et al., 2026). Common use cases identified include predictive maintenance, anomaly detection, risk interpretation, and real-time environmental scanning (Kmiecik, 2026; Kurrahman et al., 2025).

Several studies in the reviewed sample report that sensing effectiveness depends on the conversion of dispersed data into structured, reusable knowledge. Kurrahman et al. (2025) report that sensing benefits from dynamic knowledge and learning capabilities to generate green supply chain improvements. Liu and Tian (2026) describe generative capability as a higher-order knowledge process encompassing acquisition, integration, and updating. Liu et al. (2026) report that LLM integration is associated with continuous environmental interpretation and reactive cognition.

Contextual factors further moderate sensing effectiveness. Positive outcomes are consistently stronger in digitally intensive, environmentally dynamic environments: Guo et al. (2026) find resilience benefits larger in high-technology firms, while Gao et al. (2026) report green productivity gains highest in mature firms, non-heavy-polluting industries, and highly regulated contexts. In the sustainability domain specifically, GenAI-enabled processing of unstructured sustainability reports and regulatory documents supports identification of circular economy practices, waste management opportunities, and process optimization pathways (Bag et al., 2026; Kurrahman et al., 2025).

4.3.2 GenAI for Seizing Capabilities

The reviewed literature identifies GenAI as a facilitator of more agile, data-driven opportunity assessment and resource allocation in supply chains. Seizing is the mobilization of resources in response to identified opportunities, which is supported by GenAI through scenario-based analysis and multimodal data integration (Kurrahman et al., 2025). GenAI systems, instead of deterministic, historically constrained approaches, explore a variety of what-if settings in the face of uncertainty, integrating trade-offs between cost, resilience, and sustainability to expand the set of strategic choices available to decision-makers (Jackson et al., 2024; Liu & Tian, 2026).

Generative systems combine heterogeneous information to generate structured decision support outputs, which increase the speed of decisions in a complex, cross-border setting, where the time wasted in processing data directly converts to lost opportunities or uncontrolled risks (Liu et al., 2026; Jackson et al., 2024).

Generative tools synthesize heterogeneous information into structured decision support outputs, accelerating decision speed especially in complex, cross-border environments where data processing delays translate directly into missed opportunities or unmanaged risks (Liu et al., 2026; Jackson et al., 2024). The literature also documents faster operational responses as a result: firms translate analytical insights into supply chain adjustments with less lag, reducing the cost of reactive management (Guo et al., 2026; Boone et al., 2025). In international supply chain settings, GenAI further supports collaborative seizing, enabling multi-stakeholder coordination by providing predictive diagnostics, risk information, and simulation outputs accessible to distributed actors across organizational and national boundaries (Kurrahman et al., 2025; Lukács et al., 2026). Applications in supplier development and circular economy transition illustrate how GenAI helps identify and act on sustainability opportunities across partner networks (Bag et al., 2025).

4.3.3. GenAI for Reconfiguring Capabilities

The reviewed literature identifies, within the DCV, that reconfiguring represents the highest-order dimension of the continuous renewal and transformation of assets, processes, and organizational structures to maintain competitiveness in volatile environments. The reviewed literature identifies flexibility, adaptive capabilities, and eco-dynamic capabilities as key reconfiguration mechanisms that GenAI enables (Kurrahman et al., 2025).

The reviewed studies report reconfiguring most often as a continuous, process-embedded transformation rather than as episodic restructuring (Liu et al., 2026; Liu & Tian, 2026; Lukács et al., 2026). Liu and Tian (2026) describe GenAI as a dynamic knowledge engine supporting cross-generational knowledge acquisition and agile adaptability to changes in stakeholder expectations, directly with the support of green innovation and quick supply chain reconfigurations to complex environmental situations. Lukács et al. (2026) present the evidence of a particular structural mechanism, Sustainable Process Reconfiguration Capability (SPRC), within the framework of which companies redesign work processes to achieve circular and resource-efficient business processes, including waste reduction, resource optimization, and closed-loop logistics. GenAI facilitates this through generative eco-design intelligence and predictive circular planning that simulate environmental trade-offs before resource deployment. Liu et al. (2026) separately document empirical evidence that LLM work integration catalyzes a serial mediation pathway from digital process transformation to higher-order cognitive supply chain capabilities to systemic regenerative capacity, enabling firms not merely to recover from disruptions but to structurally transform following them.

4.4 Dynamic Capabilities and Sustainability Outcomes

Across the reviewed sample, a few studies report a direct, unmediated effect of GenAI adoption on sustainability outcomes. Where structural models are estimated, the effect is reported as fully or partially mediated by collaborative practice, circular-economy implementation, ethical governance routines, or higher-order capabilities (Li et al., 2024; Bag et al., 2025; Lukács et al., 2026). The strength and reported conditionality of this mediation differ across the three TBL dimensions, as set out in Sections 4.4.1–4.4.3.

4.4.1 Environmental Performance

Environmental outcomes are the most robust TBL dimension in the reviewed sample. The dominant cross-study finding is that GenAI improves the firm's capacity to identify inefficiencies, simulate greener alternatives, and reconfigure processes toward lower emissions and resource-efficient designs (Bag et al., 2026; Li et al., 2024; Lin, 2025; Lukács et al., 2026; Qin & Zhang, 2026). However, all five of these studies condition the gain on collaborative or governance routines that operationalize AI insight into collective action.

Li et al. (2024), on a Chinese Manufacturing sample, demonstrate that green supply chain collaboration and circular economy implementation fully mediate the GenAI and performance relationship, indicating that environmental benefits materialize only when AI insights are converted into collective operational routines. A parallel mechanism is documented in a US-based socio-technical study (Lukács et al., 2026), where generative eco-design intelligence and predictive circular planning strengthen SPRC, which in turn enhances socio-environmental value creation and circular supply chain resilience. The Taiwanese Unified Sustainability-Oriented Generative Intelligence (UNISONE) case (Lin, 2025) shows further that a balanced GenAI-supported strategy can simultaneously reduce carbon emissions and maintain operational performance, suggesting that environmental and efficiency objectives can be co-optimized through reconfiguration capability rather than traded off.

4.4.2 Social Performance

Across the reviewed literature, the reporting of social outcomes is far less consistent than that of environmental outcomes, due to the complex, qualitative nature of measuring the social impact. However, the literature is convergent on a specific socio-technical path through responsible AI use, ethical AI awareness, and AI-enabled stakeholder co-creation (Bag et al., 2025; Lukács et al., 2026; Shabbir and Keshtiban, 2026). The literature cautions that polycrisis conditions, institutional instability, and policy contradictions can undermine the translation of responsible AI collaboration into socio-environmental value, making social outcomes more fragile and context-dependent than environmental ones, particularly across diverse IB settings (Bag et al., 2025; Lukács et al., 2026).

Similarly, GenAI integration is not an unbiased technological upgrade; it is a socio-technical transformation. Shabbir and Keshtiban (2026) explicitly conceptualize GenAI as a socio-technical resource that is embedded within collaborative ecosystems, cautioning that without participatory governance and multi-stakeholder collaboration, GenAI is likely to contribute to increasing the asymmetries and digital divide caused by algorithms, especially in resource-constrained environments.

4.4.3 Economic Performance

Economic sustainability outcomes such as operational efficiency, financial performance, and competitive advantage are consistently shown to be indirect and capability mediated. GenAI enhances responsiveness, sourcing stability, innovation speed, and decision quality, but these benefits emerge through capability development and process integration rather than through technology adoption alone (Li et al., 2024; Lin, 2025).

Joshi et al. (2026) demonstrate that GenAI operates as a process enablement capability linking internal competencies, digital transformation, innovation, and marketing capabilities with market deliverables, while identifying a structural asymmetry. Sustainability performance is fully mediated by GenAI, but market performance remains substantially driven by direct external valuation and active dynamic capability implementation. Li et al. (2024) reinforce that the direct effect of GenAI on sustainable supply chain performance becomes statistically negligible once green supply chain collaboration and circular economy practices are controlled for, confirming that economic value requires firms to embed AI intelligence into joint planning and circular operations. Across China, the USA, India, South Africa, and Taiwan, the literature converges on the finding that economic payoffs are most durable when GenAI represents a dynamic capability that transforms supplier relationships, planning processes, and cognitive decision logic toward long-term regenerative sustainability rather than short-term efficiency maximization (Bag, 2025; Li et al., 2024; Lin, 2025).

4.5 Moderating and Contingency Factors

4.5.1 Organizational Factors

As shown in the literature, the benefits of GenAI supply chains are always based on a combination of organizational micro-foundations, as opposed to the adoption of technology itself. According to Bag (2025), the managerial GenAI literacy, responsible governance culture, GenAI experimentation culture, cognitive ambidexterity, prompt-engineering capability, and contract management competence are positively associated with flexibility and sustainability performance in the supply chain. Likewise, the study by Maghroor et al. (2025) reveals that upstream determinants of successful adoption are the commitment of leadership, strategic alignment, and structural readiness, and downstream barriers are the resistance to change, lack of finances, and misaligned incentives.

The key contingency is labor preparedness. Lack of training, low management participation, and talent shortages are symptoms of underlying organizational weaknesses, and workforce investment should be accompanied by structural preparedness (Maghroor et al., 2025). Ahmed et al. (2025) also show that GenAI integration into knowledge-sharing and decision-making is moderated by trust and collaborative organizational culture, and siloed communication and leadership disengagement negatively influence resilience gains. Another contingency that Bag (2025) adds is the presence of organizational politics, which has a negative moderation effect on the learning-performance relationship, meaning that inner power relations may inhibit the manifestation of outcomes even in the situation when GenAI effectively reinforces learning and adaptive flexibility.

4.5.2 Institutional Factors

Institutional factors operate as substantive moderators rather than passive background conditions. Regulatory ambiguity and weak cross-border harmonization, as identified by Maghroor et al. (2025) as significant environmental barriers, increase geopolitical risk, slow AI investment, and complicate responsible implementation across dispersed supply chains. It means that the usefulness of GenAI-empowered sustainability decision-making depends on the transparency and enforceability of external regulatory frameworks, an aspect that has a direct implication in the context of MNEs that run their business under heterogeneous regulatory frameworks.

Lukács et al. (2026) show a negative moderating effect of regulatory ambidexterity between AI-enabled stakeholder co-creation and socio-environmental value, meaning that concomitant pressure of compliance and anticipatory governance needs disrupt value creation under the contradictory policy signals. The same dynamic is recorded by Ahmed et al. (2025) in the context of large-scale infrastructure, where the overlapping local and federal regulatory systems add to the overall cost of coordination, but trust and organizational culture can redefine institutional complexity as an opportunity instead of a constraint. In addition to coercive regulation, normative expectations regarding responsible AI implementation are also important. Governance practices, transparency standards, and stakeholder-oriented use affect whether firms participate in substantive capability formation or adopt AI responsibly in a symbolic manner (Maghroor et al., 2025; Lukács et al., 2026).

4.5.3 Contextual Factors

Firm size, industry conditions, and geographic context further condition GenAI's capability-building potential. Organizational size is a meaningful constraint: smaller firms face greater financial barriers, infrastructure deficits, and strategic misalignment, implying that larger organizations more readily convert GenAI investments into dynamic capabilities (Maghroor et al., 2025). SMEs may require modular, collaborative, or lower-cost adoption pathways to capture comparable sustainability benefits. It is an important consideration given that SMEs constitute the majority of suppliers in most global value chains.

There is geographic heterogeneity, which brings in great differences in capability-building strength. A cross-national study indicates that, in India but not in South Africa, higher path coefficients indicate that disparities in AI preparedness, digital infrastructure, and ethical governance modify the efficiency of GenAI-enabled capability-building. Sectoral context is also important: Lukács et al. (2026), in a study of logistics, manufacturing, e-commerce, and IT companies in the USA, discovered that the generative eco-design intelligence and predictive circular planning can help to reconfigure sustainability processes, but the achievement of socio-environmental values is dependent on collaborative conditions and policy coherence.

Together, these results affirm that the translation of GenAI into sustainable supply chain outcomes is contingent based on context, i.e. the industry, the size of the firm, its digital maturity, and institutional cross-country variation, and not an effect of universal adoption (Ahmed et al., 2025; Bag, 2025; Lukács et al., 2026; Maghroor et al., 2025)

5. Discussion

This chapter elevates the findings of the SLR to the level of theoretical interpretation, conceptual integration, and research contribution. Its purpose is to answer the overarching research question: how GenAI contributes to the development of dynamic capabilities that enable sustainable supply chain performance in international business contexts, with a depth that the evidence-bound Findings chapter could not provide. The discussion is organized as follows. Section 5.1 synthesizes answers to each of the three sub-questions. Section 5.2 presents the study's three theoretical contributions, including a proposed conceptual framework. Section 5.3 develops the international business implications of the findings. Section 5.4 presents practical implications of the study. Lastly, section 5.5 reflects on the limitations and research opportunities.

5.1 Synthesis of Research Questions

5.1.1 GenAI Applications in Sustainable Supply Chain Management

A critical synthesis of the literature reviewed reveals a clear contradiction between what Generative AI (GenAI) has definitively proven able to do and what is still uncertain about the boundaries of its deployment. Primarily, the literature conclusively resolves that GenAI applications are real, fast-growing, and structurally clustered. The richest empirical data of GenAI implementation occurs in upstream supply chain operations, especially in demand forecasting, supplier intelligence, and real-time risk monitoring (Bahroun et al., 2026; Boone et al., 2025; Sonar et al., 2026). Second, the literature is united by the agreement that GenAI is essentially a cognitive augmentation mechanism and not an operational replacement mechanism. Instead of operating independently and performing physical supply chain activities, advanced generative models enhance the ability of decision-makers to interpret environmental complexity, synthesize unstructured qualitative data, and generate strategic options in volatile environments (Fosso Wamba et al., 2024; Liu & Tian, 2026; Marzi and Balzano, 2025). Third, quantitative evaluations confirm that the allocation of these applications through the Supply Chain Operations Reference

(SCOR) framework is severely skewed; deployments are highly concentrated in the information-rich Plan and Enable functions, and the domains of execution are highly loaded (Make, Return, and physical cross-border coordination) (Bahroun et al., 2026; Sonar et al., 2026).

What the literature leaves unanswered, however, reveals crucial gaps both empirically and contextually when it comes to the actual value of these technologies. The literature, in the first place, has not decided whether the strong skew in SCOR is due to true technological constraints in downstream physical performance or is simply an artifact of measurement produced by the geographic concentration of empirical work. It is not clear whether the inability of GenAI to perform execution functions is an absolute technological limit or the symptom of fragmented digital infrastructure and institutional gaps in developing contexts (Bag et al., 2025; Bahroun et al., 2026; Lin et al., 2025).

Moreover, the literature indicates that there is a strong contradiction with the achievement of Triple Bottom Line (TBL) environmental outcomes. Although the literature widely records sustainability-specific applications such as acceleration of Life Cycle Assessments (LCA) and simulation of circular eco-designs, more evidence has not been established on whether these tools deliver verified and tangible environmental benefits or whether they are primarily the means of reducing corporate reporting and compliance costs. Without a strong sense of ESG sensemaking and ethical governance, scholars warn that the application of GenAI risks creating a sustainability information overload, which could be exploited to facilitate superficial, so-called greenwashing, instead of systematic ecological recovery (Bag et al., 2026; Bahroun et al., 2026; Qin & Zhang, 2026). Lastly, the remaining literature has not discussed how the current footprint of isolated, planning-intensive applications can effectively be scaled to achieve network-level transformation, which requires active and AI-enabled co-creation of value across different stakeholders and regulatory jurisdictions (Lukács et al., 2026; Sonar et al., 2026).

The first research question (RQ1) regarding GenAI applications to sustainable supply chain management is therefore responded to with a qualified yes. Indeed, GenAI apps are on the rise and are moving towards a steady pattern of improving upstream sensing and predictive planning abilities. Nevertheless, their richness and effectiveness in operations are not universally ensured; instead, they are strictly limited by the level of digital infrastructure of the host country, variation of cross-border jurisdictional environments, and immaturity of the applications.

5.1.2 How GenAI supports dynamic capabilities

The reviewed literature reveals an explicit asymmetry across the three dimensions DCV, and the asymmetry is best read as a sequencing logic rather than a list of independent effects. Sensing is the most immediate and most consistently documented pathway. Across studies, it aligns directly with GenAI's native strengths in synthesis, pattern recognition, and scenario generation, supporting the scanning of diverse data sources, the identification of weak signals, and the detection of patterns relevant to geopolitical risk, demand volatility, sustainability mandates, and supplier performance (Bahroun et al., 2026; Kurrahman et al., 2025; Liu & Tian, 2026). The studies, however, diverge on how universal this gain is. Kurrahman et al. (2025) report sensing as the strongest of the three capability dimensions in green supply chain settings, with the largest causal coefficient. This finding can be qualitatively explained by Guo et al. (2026) and Gao et al. (2026): sensing-related resilience and green-productivity benefits concentrate in high-technology companies, established companies, and highly regulated regions, and decay sharply in data-poor or regulation-ambiguous environments (Bag et al., 2025; Lin et al., 2025). Sensing is strong, therefore in direction but conditional in magnitude, the boundary conditions that the more modern capability-only type of studies are apt to obscure.

Seizing is the conditional middle of the asymmetry. GenAI assists managers in evaluating their strategic choices, simulates complex trade-offs, and serves as a collaborative decision-support partner that can expand the available solution space (Boone et al., 2025; Jackson et al., 2024; Liu et al., 2026). However, there are two boundary conditions between high-functioning and weak seizing applications. The first is maturity of governance: Liu et al. (2026) and Sonar et al. (2026) report that the ability to seize benefits depends on the AI governance routines, trust, and explainability mechanisms which reduce the risk of data-related hallucinations and algorithmic obscurement; otherwise, the results of the scenarios will not be sufficiently trusted to be acted on. The second one is task-technology alignment: Boone et al. (2025) and Guo et al. (2026) report on strong gains where GenAI assists well-defined, time-pressured decisions (rerouting, reallocation), but markedly weaker effects where decisions are open-ended or politically contentious. The seizing pathway thus has much more variability in effect sizes across studies than does sensing.

Reconfiguring is the most demanding dimension and the least uniformly developed. It supports the redesign of operational processes and supply chain networks, but materializes only where firms can institutionalize learning, redesign routines, and coordinate change across organizational boundaries (Kmiecik, 2026; Liu et al., 2026; Lukács et al., 2026).

The two empirically different constructs of the literature, that is, the Sustainable Process Reconfiguration Capability by Lukács et al. (2026) and the supply chain regenerative capability by Liu et al. (2026), agree on the underlying knowledge-based process but differ in the unit of analysis (process-level versus system-level transformation). The similarity between them is that the highest organizational and digital maturity of the three dimensions is required, which explains why the evidence of reconfiguration is concentrated in large, digitally mature companies in China and the United States and is mostly absent in SME and emerging-market studies (Bag et al., 2025; Maghroor et al., 2025).

Putting together, these patterns suggest a sequencing logic the operations-management literature has not previously made explicit: GenAI builds sensing capability quickly, seizing capability conditionally on governance and task fit, and reconfiguring capability only where the prior two are institutionalized. This sequence is itself moderated by international business factors — institutional heterogeneity, digital divides, and MNE coordination — which compress or extend each step depending on subsidiary context (Bag et al., 2025; Bahroun et al., 2026; Lin et al., 2025).

GenAI supports the development of dynamic capabilities through differentiated mechanisms across sensing, seizing, and reconfiguring. In sensing, GenAI acts as a cognitive augmentation tool, helping firms to scan diverse data sources, identify weak signals, and detect patterns relevant to geopolitical risk, demand volatility, sustainability mandates, and supplier performance (Bahroun et al., 2026; Boone et al., 2025; Lin et al., 2025). In seizing, it helps managers in assessing strategic options, and simulating complex trade-offs, acting as a collaborative decision-support partner that expands the available solution space (Bahroun et al., 2026; D.Y. Liu et al., 2026; Marzi & Balzano, 2025). In reconfiguring, it supports the redesign of operational processes and supply chain networks. But only if firms can institutionalize learning, redesign routines, and coordinate change across their boundaries.

This study also highlights that GenAI does not strengthen all capabilities equally. The review indicates that sensing is the most immediate and robust pathway because it aligns closely with GenAI's strengths in synthesis, pattern recognition, and scenario generation (Bahroun et al., 2026; Fosso Wamba et al., 2023). Conversely, transition to seizing requires stronger complementary conditions, including trust, robust artificial intelligence governance, and precise task-technology alignment to overcome algorithmic opacity and hallucination risks (D.Y. Liu et al., 2026; Sonar et al., 2026). Finally, reconfiguring requires the greatest degree of organizational and digital maturity because it depends on translating analytical possibilities into structural and relational change (Kmiecik, 2026; W. Liu et al., 2026).

5.1.3 How dynamic capabilities translate into sustainability outcomes

Dynamic capabilities translate GenAI use into sustainable supply chain outcomes by enabling firms to detect sustainability-relevant changes, evaluate appropriate responses, and implement process-level adjustments (Kurrahman et al., 2025; D.Y. Liu et al., 2026). The literature suggests that sustainability outcomes are strongest where GenAI-enabled capabilities are linked to specific, value-generating organizational practices such as green supply chain collaboration, circular economy implementation, adaptive supply chain planning, and AI-augmented supplier development (Li et al., 2024; Boone et al., 2025; Bag et al., 2025). This operationalization from insight into action explains why mere technological adoption is a fundamentally insufficient driver of performance; sustainable transformation requires the organizational capability to filter, contextualize, and enact AI-generated intelligence (Bag et al., 2026; Liu & Tian, 2026).

However, the systematic review also indicates that the translation from dynamic capabilities to sustainability outcomes is highly uneven across the TBL (Bahroun et al., 2026). Environmental and economic performance, such as greenhouse gas emissions reduction, waste management, and cost-effectiveness, are far more advanced and explicitly reported in the current empirical landscape (Bahroun et al., 2026; Boone et al., 2025). This does not mean social sustainability is irrelevant but highlights a methodological and theoretical gap in the literature. There are still no equally well-developed empirical measures and governance levers to assess social outcomes, often overlooking participatory oversight, power imbalances, and digitally excluded areas (Bahroun et al., 2026; Shabbir & Keshtiban, 2026).

5.2 Theoretical Contribution

This thesis makes three interrelated theoretical contributions. First, it extends the Dynamic Capabilities View by showing that GenAI should not be conceptualized simply as an operational tool or digital input, but as a higher-order generative meta-capability whose value is expressed through the capability-building processes it enables (Liu & Tian, 2026; Bag et al., 2025). In this respect, the review moves beyond studies that describe GenAI use cases and instead explains how GenAI reshapes the micro foundations of sensing, seizing, and reconfiguring by expanding environmental scanning, broadening scenario evaluation, and supporting knowledge-intensive forms of process renewal (Kurrahman et al., 2025; Jackson et al., 2024; Liu et al., 2026).

This reframing is significant because it moves from the focus of technology adoption to capability building. The uses of GenAI in supply chains have been documented in previous studies and reviews, but not to the same extent as explaining the various strategic outcomes for the same technology, depending on the specific context and firm. (Bahroun et al., 2026; Jackson et al., 2024). This thesis explains how the value of technology is not a given and that GenAI is a meta-capability, not a neutral technology. This hinges on the businesses' ability to integrate AI-generated results into their operations in a coordinated way, which requires a high level of governance, absorptive routines, and inter-organizational learning mechanisms (Li et al., 2024; Liu et al., 2026; Maghroor et al., 2025).

5.2.1 Extending the DCV for the GenAI Era

The central theoretical contribution of this review is a systematic extension of Teece et al.'s (1997) DCV to the context of GenAI-enabled international supply chains. The DCV, in its original formulation, conceptualizes sensing, seizing, and reconfiguring as hierarchically organized organizational capabilities grounded in managerial cognition, organizational routines, and asset orchestration. This review demonstrates that GenAI fundamentally reshapes the micro-foundations of all three dimensions in ways that the original framework did not anticipate.

In the sensing dimension, GenAI does not merely enhance existing scanning routines; it creates new micro-foundations for environmental intelligence through large-scale unstructured data processing, automated signal interpretation, and continuous knowledge updating (Liu et al., 2026; Kurrahman et al., 2025). In the seizing dimension, GenAI transforms strategic evaluation from a cognitive, managerially bounded process into a computationally augmented, scenario-rich process that operates with lower latency and greater analytical breadth (Jackson et al., 2024). In the reconfiguring dimension, the emergence of SPRC and regeneration capability as distinct, empirically supported constructs suggests that GenAI enables a qualitatively new class of reconfiguration, not episodic asset reallocation but continuous, knowledge-driven organizational transformation (Lukács et al., 2026; Liu et al., 2026).

Importantly, this review also establishes that GenAI itself operates as a dynamic capability, or more precisely, as what Liu and Tian (2026) term a generative capability: a higher-order meta-capability that enables and amplifies the development of sensing, seizing, and reconfiguring capabilities. This framing distinguishes GenAI from ordinary digital tools, which support existing capabilities and positions it as a second-order dynamic capability whose value is expressed through the first-order capabilities it enables. This distinction has significant implications: it shifts the unit of analysis from GenAI adoption to GenAI-enabled capability development and redirects managerial attention from technology deployment to organizational capability building.

5.2.2 Integrating the Knowledge-Based View with DCV

A secondary theoretical contribution of this review is the identification of Knowledge-Based View (KBV) integration as a necessary extension of DCV when applied to GenAI contexts. Liu and Tian (2026) explicitly theorize generative capability through a DCV-KBV integration, showing that GenAI's impact on circular supply chain practices operates through a serial mediation pathway; generative capability, iterative innovation, and circular practices, that is fundamentally a knowledge acquisition, inheritance, and updating process. This finding suggests that understanding how GenAI builds dynamic capabilities requires attention not just to organizational structures and routines (DCV's traditional focus) but to knowledge flows, knowledge reconfiguration processes, and the cognitive architecture of organizational learning.

This DCV-KBV integration is particularly relevant in the international business context, where knowledge heterogeneity across geographies, institutional environments, and technology maturity levels is a defining feature. GenAI's capacity to process multi-language, multi-format, multi-context knowledge sources make it particularly suited to addressing the knowledge integration challenges that characterize MNE supply chain management, though the organizational learning infrastructure to leverage this capacity varies substantially across firm types and national contexts.

5.2.3 Advancing the International Business View of GenAI-Enabled Supply Chains

The third theoretical contribution of this review is the advancement of the international business view by reclassifying GenAI not as an isolated domestic operational technology but as a multinational capability infrastructure whose performance is tightly constrained by institutional differences, digital divides, and coordination problems of the multinational enterprise (MNE). To date, the research on GenAI in mainstream supply chain management has been limited to a single country and industry-based empirical contexts (Bahroun et al., 2026; Li et al., 2024; Lukács et al., 2026) and has therefore hugely underestimated the global nature of capability formation. Drawing on evidence from cross-national and regionally comparative studies (Bag et al., 2025; Lin et al., 2025) in conjunction with the DCV, this review shows that the link between GenAI adoption and sustainable performance is moderated by International Business (IB) factors that would otherwise be absent from single-country studies. In particular, capability development is consistently interrupted by jurisdictional fragmentation in environmental, social, and governance (ESG) policies, significant digital infrastructure inequalities between international subsidiaries, inter-regional data-governance tensions, and cultural differences in experimentation with algorithms (Maghroor et al., 2025; Sonar et al., 2026).

This review contributes to the international supply chain literature in three ways. First, it builds on the dynamic capabilities perspective in international business by identifying GenAI as a meta-capability whose orchestration must be strategically varied rather than replicated across multinational enterprise (MNE) subsidiaries, explicitly considering subsidiary digital capability (Bahroun et al., 2026). Second, it introduces key moderators from IB - such as regenerative policy ambidexterity, digital-infrastructure asymmetry, and cross-jurisdictional ESG variation - into the GenAI-sustainability debate that has previously been considered context-neutral by the operations management literature (Bag et al., 2025; Lukács et al., 2026; Maghroor et al., 2025). Third, it renews the empirical bias of GenAI studies in digitally advanced economies to a significant theoretical problem rather than mere sample bias. The spatial skew itself indicates the significant digital-divide moderator in the conceptual framework and where future international supply chain research must focus to avoid further digital inequalities in global value chains (Bahroun et al., 2026; Lin et al., 2025). These theoretical innovations position GenAI as a socio-technical outsider that international supply chain research can no longer overlook in its traditional discussions of global value chains, MNE coordination, and cross-jurisdictional sustainability governance.

5.2.4 Conceptual Framework

Drawing on the systematic synthesis of the reviewed literature, this study proposes an integrative conceptual framework (Figure 5) that maps the capability-mediated pathway from GenAI adoption to sustainable supply chain performance in international business contexts.

The first component, GenAI Enabling Inputs, comprises the technology-level resources such as LLMs, RAG systems, generative digital twins, NLP-based ESG analytics, and agentic AI that supply the raw computational and knowledge-processing capacity for capability development (Bahroun et al., 2026; Boone et al., 2025; Jackson et al., 2024). Crucially, these inputs are not treated as exogenous tools but as the substrate from which knowledge acquisition, integration, and updating routines emerge, which is the KBV insight that Liu and Tian (2026) operationalize as “generative capability.” This is where the framework explicitly integrates the Knowledge-Based View: GenAI inputs become organizationally meaningful only when coupled with knowledge-management routines that turn unstructured, multi-source data into reusable organizational knowledge.

The second component, Dynamic Capabilities Development, is the three-dimensional capabilities space (sensing, seizing, reconfiguring) that GenAI enhances, with Sustainable Process Reconfiguration Capability (SPRC) and regenerative capability positioned as advanced expressions of the reconfiguring dimension (Kurrahman et al., 2025; Lukács et al., 2026; Liu et al., 2026). Knowledge flows not just routines but moves firms along this capability hierarchy, which is why the DCV–KBV integration is essential rather than ornamental.

The third component, TBL Sustainability Outcomes, captures environmental, social, and economic performance and is reached only indirectly: the reviewed empirical literature consistently reports that GenAI's effect on sustainability is mediated through dynamic capabilities and operationalized through green supply chain collaboration, circular economy implementation, and stakeholder co-creation (Li et al., 2024; Bag et al., 2025; Lukács et al., 2026).

The fourth component, Moderating Context, conditions every link in the model and is organized at three levels: organizational (governance readiness, digital dexterity, leadership commitment), institutional (regulatory clarity, AI-governance maturity, cross-jurisdictional ESG harmonization), and contextual (firm size, industry, geographic digital maturity) (Ahmed et al., 2025; Bag, 2025; Maghfoor et al., 2025; Lin et al., 2025). The IB dimension is embedded in this fourth component: institutional heterogeneity, digital divides, and MNE subsidiary coordination operate as cross-cutting moderators that distinguish international from purely domestic supply chain dynamics.

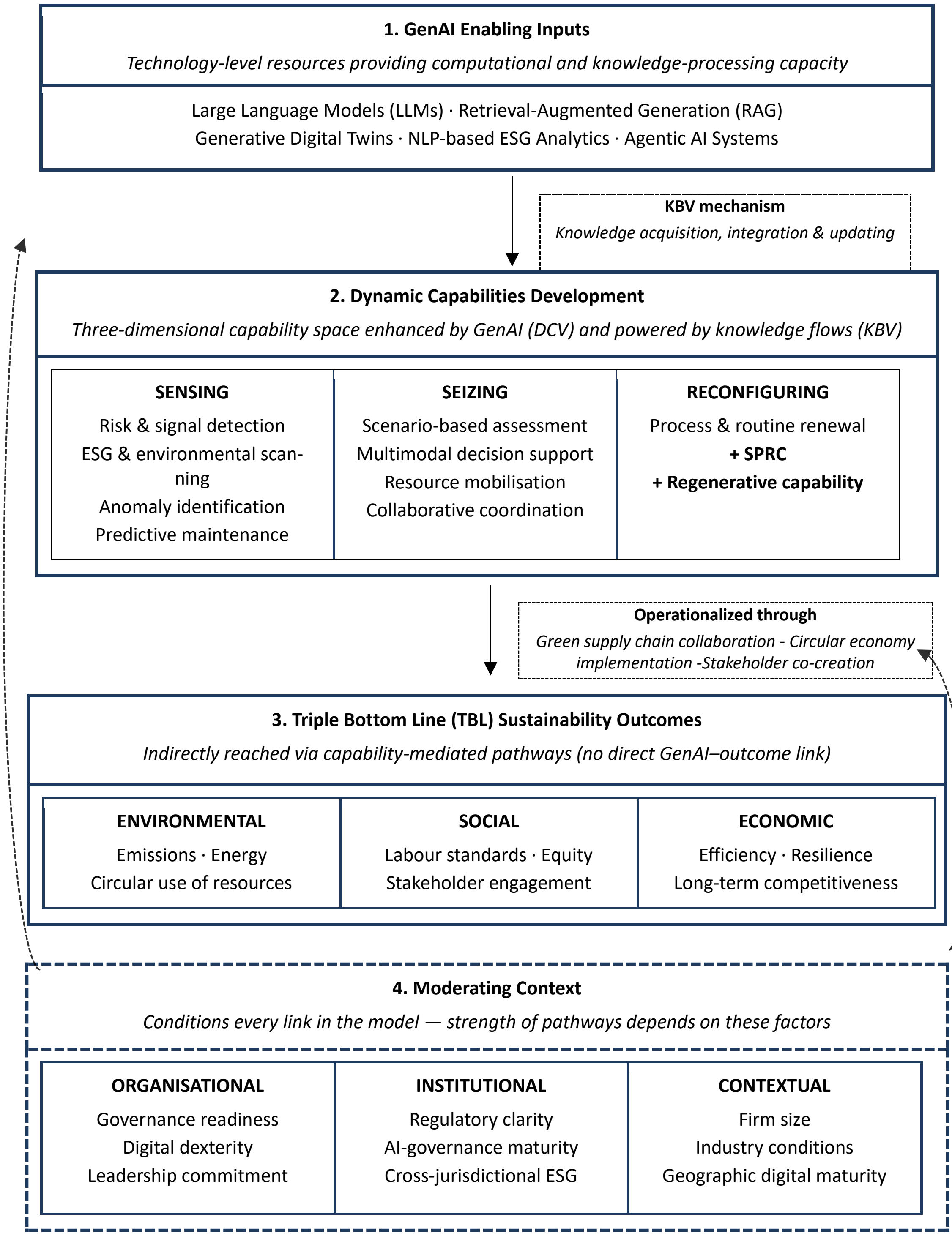

Figure 5: Conceptual Framework based on Theoretical foundations: Teece (1997, 2007). Adapted with insights from Liu & Tian (2026); Lukács et al. (2026); Bag et al. (2025); Lin et al. (2025).

Together, the four components yield three structural claims that the reviewed literature supports:

1. The GenAI–sustainability link is indirect and mediated by dynamic capabilities built through DCV–KBV mechanisms, not by technology adoption alone.
2. The strength of the GenAI–capability link itself is conditional on the moderating context, so identical inputs produce uneven capability gains across firms and regions.
3. The IB context constitutes a distinct, cross-cutting moderator that defines the boundary between international and domestic supply chain dynamics and that has been under-theorized in operations-management treatments of GenAI.

5.3 International Business Implications of the Findings

5.3.1 Institutional Heterogeneity and Regulatory Fragmentation

The International Business literature has long recognized that institutional heterogeneity, such as variation in regulatory regimes, governance quality, and formal institutional frameworks across borders, represents a fundamental source of complexity for Multinational Enterprises (Teece, 2007, 2025; Teece et al., 1997). The thematic synthesis demonstrates that GenAI does not resolve this complexity; rather, it refracts it. The delivery of socio-environmental value through the GenAI-enabled sensing and seizing capabilities is subject to the regulatory environment where GenAI technologies are applied (Bag et al., 2026; W. Liu et al., 2026; Lukács et al., 2026). In environments with high regulatory clarity, robust regulatory governance provides the regulatory framework to enable GenAI-powered compliance automation, ESG reporting, and sustainability monitoring to be highly precise, seamlessly translating efficient decision-making into the defined value outcomes (Bag et al., 2026; Boone et al., 2025). Conversely, in regulatory-fragmented or ambiguous environments, these same generative capabilities encounter severe friction. Disparate cross-border data laws and evolving compliance norms increase data processing overhead, reduce prediction reliability, and heighten governance uncertainty, collectively constraining the effective deployment of AI for sustainable supply chain performance (Bag et al., 2025; Maghroor et al., 2025).

5.3.2 Digital Divides and Uneven Capability Development

The geographic distribution of the reviewed literature is heavily concentrated in China and India, with limited representation of Sub-Saharan Africa, South-East Asia, Latin America, and Central Europe, which is not merely a scholarly gap. It reflects a real-world asymmetry in GenAI readiness and digital infrastructure that has direct consequences for international supply chain sustainability. Lin et al. (2025) demonstrate that GenAI's sensing effectiveness is directly moderated by data quality and the availability of digital infrastructure, with data-poor environments yielding shorter warning windows, higher false-positive rates, and reduced reconfiguration capacity. Bag et al. (2025) document higher capability-building path coefficients in India than in South Africa, suggesting that the strength of GenAI's contribution to dynamic capabilities varies systematically with national digital maturity.

These findings point to a risk that the IB literature on digital transformation has flagged, but the GenAI-supply chain literature has not yet fully theorized: the technology may amplify existing digital divides rather than bridging them. Large, digitally resourced MNEs and their suppliers in digital-infrastructure-rich environments will build GenAI-enabled dynamic capabilities faster and more effectively than SMEs, domestic firms, and supply chain actors in digitally lagging regions. If left unaddressed, this asymmetry could entrench existing competitive inequalities in global supply chains under the guise of technological progress.

5.3.3 MNEs Strategy and GenAI Deployment Across Organizational Boundaries

This review identifies a critical tension in how Multinational Enterprises (MNEs) can and should deploy GenAI capabilities across their international operations. The strategic case for centralization is compelling: deploying standardized GenAI platforms, sharing Large Language Model (LLM) infrastructure, and consolidating data governance reduces duplication and enables economies of scale in capability building (Ahmed et al., 2025; Boone et al., 2025; Maghroor et al., 2025; Sonar et al., 2026). However, the synthesized literature demonstrates that the case for localization is equally imperative. Global algorithmic governance frameworks built around strict data-protection regimes such as the GDPR illustrate the regulatory mismatch identified in section 5.3.1 - when applied in developing markets with evolving standards, they generate high data-processing costs and regulatory uncertainty (Bag, 2025; Maghroor et al., 2025).

Behavioral and cultural differences compound these regulatory and infrastructural barriers. Organizational cultures supporting GenAI experimentation and trust at the headquarters level often face resistance or precarious adoption in cross-border subsidiaries with different professional norms and labor dynamics (Ahmed et al., 2025; Bag et al., 2025). The appropriate organizational response, what Teece (2007) conceptualizes as effective "asset orchestration" across the MNE +6network, is therefore neither uniform global deployment nor fragmented local adaptation, but a context-sensitive architecture that formalizes high-level ethical and governance standards while permitting capability deployment to vary with institutional, cultural, and digital conditions (Bag et al., 2026; Bahroun et al., 2026; Lukacs et al., 2026). This balance between global cognitive automation and decentralized, context-sensitive capability building remains underdeveloped in the current international operations management literature.

5.4 Practical Implications

5.4.1 For Supply Chain Managers

The most practical takeaway for supply chain practitioners is that GenAI's sustainability performance impact is indirect (capability-mediated). Supply chain managers who adopt GenAI as a data management or reporting tool without investing in the collaborative, governance, and operational capabilities required to translate the AI insights into collective supply chain decision-making will not achieve the full potential for improving sustainability performance described in the literature. The findings from Li et al. (2024), Lukács et al. (2026), and Lin (2025) show that companies with the best sustainability performance are those that use GenAI to enable green supply chain collaboration and circular economy practices - not those that simply use GenAI.

In practice, this means that GenAI deployment should be supported with three forms of organizational investment:

1. Governance infrastructure - policies on AI ethics, data provenance protocols, human oversight, and explainability.
2. Collaborative capability building - joint planning systems, supplier development initiatives, and inter-organizational frameworks for ESG data sharing; and
3. Workforce development - not only technical AI literacy but also strategic AI judgement - the ability to discern when GenAI insights require human corroboration and when they can be acted on.

5.4.2 For MNE Executives and International Operations Leaders

For MNE leaders, the IB-specific findings of this review point to three strategic priorities. First, the design of cross-border GenAI governance architectures that can accommodate institutional heterogeneity is a first-order strategic priority, not a compliance afterthought. Second, digital infrastructure investment in data-poor subsidiary environments is a prerequisite for GenAI capability building in those regions. In its absence, GenAI deployment will generate capability asymmetries that undermine supply chain coordination and sustainability performance. Third, the contextually differentiated approach to GenAI deployment, such as standardizing governance principles while adapting capability deployment to local conditions, requires a strategic orchestration competence that should be explicitly developed at the headquarters level.

5.4.3 For Policymakers and International Institutions

The findings of this review have direct implications for policy design at national and international levels. The regulatory fragmentation documented across jurisdictions creates barriers to responsible GenAI adoption in supply chains that individual firms cannot resolve unilaterally. International institutions and national governments should prioritize: (1) harmonized ESG disclosure frameworks that reduce MNE compliance burden while enabling GenAI-based cross-jurisdictional sustainability monitoring; (2) digital infrastructure investment in emerging markets and digitally lagging regions to prevent the entrenchment of GenAI-driven competitive asymmetries; and (3) regulatory sandboxes and industry consortia frameworks that enable responsible AI experimentation and governance learning in supply chain contexts, as proposed by Maghroor et al. (2025).

5.5 Limitations and Future Research Directions

There are a number of limitations that constrain the generalizability of the current study and highlight opportunities for future research. While the study reviews 35 empirical and conceptual papers, the body of literature is geographically limited to Asia (mostly China and India), with little input from Africa, North America, and Europe. The framework should be tested in a wider range of countries to determine the institutional boundary conditions.

Moreover, the studies reviewed are mostly cross-sectional, which limits our ability to make causal claims about the dynamics of GenAI-enabled capability development. Longitudinal research is required to determine whether the sensing, seizing, and reconfiguring relationship is indeed hierarchical and sequential or whether the three processes co-evolve. Finally, as GenAI technology rapidly evolves, especially with the introduction of agentic AI systems, multimodal models, and domain-specific LLMs, some of the findings may be out of date or need extension by developments that are not yet reflected in the peer-reviewed literature.

Table 3 synthesizes the key research gaps identified through this review into a structured future research agenda.

Research Gap	Theoretical Lens	Suggested Methodology	Relevant Studies
How do GenAI capabilities develop sequentially across sensing–seizing–reconfiguring dimensions over time?	DCV, longitudinal capability theory	Longitudinal case studies; panel data analysis	W. Liu et al. (2026); D.Y. Liu et al. (2026); Bag et al. (2025)
What governance architectures allow MNEs to deploy GenAI capabilities consistently across institutionally heterogeneous subsidiary networks?	Institutional theory, DCV, agency theory	Comparative MNE case studies; survey-based SEM across regions	Bahroun et al. (2026); Bag et al. (2025); Sonar et al. (2026)
How do digital divides and SME resource constraints moderate the GenAI → dynamic capability pathway across different economy types?	Resource-based view, institutional voids	Multi-country comparative studies; SME-focused empirical research	Gao et al. (2026); Bahroun et al. (2026); Maghroor et al. (2025)
What is the role of agentic AI and multimodal models in enabling higher-order supply chain reconfiguration capabilities?	DCV, automation theory, cognitive science	Experimental designs; simulation studies	Bahroun et al. (2026) ;
How does ethical GenAI governance (DHO, responsible AI deployment) moderate the social sustainability outcomes pathway?	Ethical theory, DCV, COR theory	Time-lagged survey research; multi-country analysis	Lukács et al. (2026); Shabbir and Keshtiban (2026)

Research Gap	Theoretical Lens	Suggested Methodology	Relevant Studies
Can GenAI-enabled ESG analytics reliably support cross-jurisdictional sustainability reporting across divergent regulatory frameworks?	Institutional theory, information processing theory	Multi-case regulatory analysis; audit studies	Bag (2026)

Table 3. Future Research Agenda

6. Conclusion

This discussion chapter has elevated the systematic findings of Chapter 4 into a coherent theoretical contribution and practical guidance for scholars, managers, and policymakers. The central argument advanced is that GenAI functions as a meta-capability, which is a second-order dynamic capability that amplifies organizational sensing, seizing, and reconfiguring capabilities but only when embedded within governance-ready, collaboration-oriented, and institutionally informed organizational contexts. The sustainability benefits of GenAI are not inherent in the technology; they are generated by the dynamic capabilities it enables and the supply chain practices through which those capabilities are operationalized.

From an international business perspective, this review contributes a theoretically grounded understanding of why GenAI's supply chain sustainability value varies systematically across national and organizational contexts. Institutional heterogeneity, digital divides, regulatory fragmentation, and MNE subsidiary coordination challenges are not peripheral concerns. In fact, they are central determinants of whether and how GenAI translates into sustainable supply chain outcomes in the global economy. Addressing these challenges requires not only organizational capability building but systemic governance innovation at the industry, national, and international institutional levels.

The conceptual framework discussed in Section 5.2.3 will provide a basis for future theoretically sound, culturally sensitive, and actionable research on GenAI and sustainable supply chain management.

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References

Agyabeng-Mensah, Y., Afum, E., & Baah, C. (2024). Stakeholder pressure and circular supply chain practices: Moderating roles of environmental information exchange capability and circular innovation orientation. *Business Strategy and the Environment*, *33*(6), 5703–5720. https://doi.org/10.1002/bse.3779

Ahi, P., & Searcy, C. (2015). Assessing sustainability in the supply chain: A triple bottom line approach. *Applied Mathematical Modelling*, *39*(10–11), 2882–2896. https://doi.org/10.1016/j.apm.2014.10.055

Ahmed, Q., Sumbal, M. S., & Lee, C. K. M. (2025). Exploring the role of generative AI to enhance knowledge management capabilities for improved supply chain resilience in large-scale initiatives. *International Journal of Engineering Business Management*, *17*, 18479790251399882. https://doi.org/10.1177/18479790251399882

Aslam, J., Saleem, A., & Lai, K.-H. (2025). Supply Chain Management in the Era of Generative AI (ChatGPT): Technology Fit and Psychological Drivers of Adoption. *IEEE Transactions on Engineering Management*, *72*, 3817–3831. https://doi.org/10.1109/TEM.2025.3605823

Bag, S. (2025). From Prompts to Performance: How Generative AI is Reshaping Supply Chain Flexibility. *Global Journal of Flexible Systems Management*. https://doi.org/10.1007/s40171-025-00453-z

Bag, S., Rahman, M. S., Routray, S., & Sreedharan, V. R. (2025). Human-Centric Generative AI in Circular Supply Chains: Theoretical Insights From Ethics, Dynamic Capabilities, and Resource Conservation. *Business Strategy and the Environment*, bse.70280. https://doi.org/10.1002/bse.70280

Bag, S., Srivastava, G., Routray, S., & Chiarini, A. (2026). Generative AI, ESG Sensemaking, and Environmental Performance: An OIPT Perspective. *Business Strategy and the Environment*, bse.70520. https://doi.org/10.1002/bse.70520

Bahroun, Z., Saihi, A., As'ad, R., & Tanash, M. (2026). A systematic analysis of generative artificial intelligence for supply chain transformation. *Supply Chain Analytics*, *13*, 100188. https://doi.org/10.1016/j.sca.2025.100188

Bhattacharya, S., Govindan, K., Ghosh Dastidar, S., & Sharma, P. (2024). Applications of artificial intelligence in closed-loop supply chains: Systematic literature review and future research agenda. *Transportation Research Part E: Logistics and Transportation Review*, *184*, 103455. https://doi.org/10.1016/j.tre.2024.103455

Boone, T., Fahimnia, B., Ganeshan, R., Herold, D. M., & Sanders, N. R. (2025). Generative AI: Opportunities, challenges, and research directions for supply chain resilience. *Transportation Research Part E: Logistics and Transportation Review*, *199*, 104135. https://doi.org/10.1016/j.tre.2025.104135

Chehbi Gamoura, S., Damand, D., Lahrichi, Y., & Saikouk, T. (2025). AI-process integrative framework for driving deep digital supply chain transformation. *Supply Chain Forum: An International Journal*, 1–15. https://doi.org/10.1080/16258312.2025.2468147

Dubey, R., Gunasekaran, A., & Papadopoulos, T. (2024). Benchmarking operations and supply chain management practices using Generative AI: Towards a theoretical framework. *Transportation Research Part E: Logistics and Transportation Review*, *189*, 103689. https://doi.org/10.1016/j.tre.2024.103689

Eisenhardt, K. M., & Martin, J. A. (2000). Dynamic capabilities: What are they? *Strategic Management Journal*, *21*(10-11), 1105–1121. https://doi.org/10.1002/1097-0266(200010/11)21:10/11%3C1105::AID-SMJ133%3E3.0.CO;2-E

Etemad, H. (2022). Towards an integrated and longitudinal life-cycle framework of international entrepreneurship: Exploring entrepreneurial orientation, capabilities, and network advantages overcoming barriers to internationalization. *Journal of International Entrepreneurship*, *20*(4), 503–536. https://doi.org/10.1007/s10843-022-00324-z

Feuerriegel, S., Hartmann, J., Janiesch, C., & Zschech, P. (2024). Generative AI. *Business & Information Systems Engineering*, *66*(1), 111–126. https://doi.org/10.1007/s12599-023-00834-7

Fosso Wamba, S., Guthrie, C., Queiroz, M. M., & Minner, S. (2024). ChatGPT and generative artificial intelligence: An exploratory study of key benefits and challenges in operations and supply chain management. *International Journal of Production Research*, *62*(16), 5676–5696. https://doi.org/10.1080/00207543.2023.2294116

Gao, X., Wang, X., & Sethanan, K. (2026). How does supply chain digitalisation affect corporate green total factor productivity? The roles of dynamic capabilities and ChatGPT. *International Journal of Logistics Research and Applications*, 1–20. https://doi.org/10.1080/13675567.2026.2613897

Govindan, K., Khodaverdi, R., & Jafarian, A. (2013). A fuzzy multi criteria approach for measuring sustainability performance of a supplier based on triple bottom line approach. *Journal of Cleaner Production*, *47*, 345–354. https://doi.org/10.1016/j.jclepro.2012.04.014

Helo, P., & Hao, Y. (2021). Artificial Intelligence in Operations Management and Supply Chain Management: an Exploratory Case Study. *Production Planning & Control*, *33*(16), 1–18. Tandfonline. https://www.tandfonline.com/doi/full/10.1080/09537287.2021.1882690

Hemlata Gangwar, Shameem, M., Patel, S., Koohang, A., & Sharma, A. (2025). Understanding determinants of GenAI usage and its effect on SCM performance using dynamic capability view. *Industrial Management & Data Systems*. https://doi.org/10.1108/imds-08-2024-0773

Jackson, I., Ivanov, D., Dolgui, A., & Namdar, J. (2024). Generative artificial intelligence in supply chain and operations management: A capability-based framework for analysis and implementation. *International Journal of Production Research*, *62*(17), 6120–6145. https://doi.org/10.1080/00207543.2024.2309309

Joshi, Y., Almugren, I., Sharma, V. K., & Imre, G. (2026). Does generative AI affect firm sustainability and market performance? Implications for information systems practitioners. *Journal of Enterprise Information Management*, 1–21. https://doi.org/10.1108/jeim-10-2025-1079

Khan, S. A. R., Yu, Z., Golpira, H., Sharif, A., & Mardani, A. (2021). A state-of-the-art review and meta-analysis on sustainable supply chain management: Future research directions. *Journal of Cleaner Production*, *278*, 123357. https://doi.org/10.1016/j.jclepro.2020.123357

Kmiecik, M. (2026). Integrating third-party logistics (3PL), forecast accuracy and emission management in triadic supply chains − a large language model-based approach. *Information Sciences*, *735*, 123084. https://doi.org/10.1016/j.ins.2026.123084

Kurrahman, T., Tsai, F. M., Lim, M. K., Sethanan, K., & Tseng, M.-L. (2025). Generative AI capabilities for green supply chain management improvement: Extended dynamic capabilities view. *International Journal of Logistics Research and Applications*, 1–28. https://doi.org/10.1080/13675567.2025.2479006

Le, T. T., & Behl, A. (2024). Linking Artificial Intelligence and Supply Chain Resilience: Roles of Dynamic Capabilities Mediator and Open Innovation Moderator. *IEEE Transactions on Engineering Management*, *71*, 8577–8590. https://doi.org/10.1109/TEM.2023.3348274

Li, L., Zhu, W., Chen, L., & Liu, Y. (2024). Generative AI usage and sustainable supply chain performance: A practice-based view. *Transportation Research Part E: Logistics and Transportation Review*, *192*, 103761. https://doi.org/10.1016/j.tre.2024.103761

Lin, K.-Y. (2025). Generative artificial intelligence–driven sustainable supply chain management: A UNISONE framework for smart logistics and predictive analytics under Industry 5.0. *International Journal of Logistics Research and Applications*, 1–32. https://doi.org/10.1080/13675567.2025.2540855

Lin, K.-Y., Wu, S.-Y., & Matsuno, K. (2025). Generative AI-Driven resilience in supply chain management: UNISONE framework for disruption modelling and capacity optimisation. *International Journal of Production Research*, 1–26. https://doi.org/10.1080/00207543.2025.2574412

Liu, W., Chotia, V., Wang, L., Sharma, P., Albishri, N., & Dash, S. (2026). Intelligence by design: Large language model work integration as strategic enablers for supply chain regeneration through digital and cognitive capabilities. *Technological Forecasting and Social Change*, *224*, 124497. https://doi.org/10.1016/j.techfore.2025.124497

Liu, Y., & Tian, H. (2026). How can generative artificial intelligence empower circular supply chain practices? Evidence from Chinese companies. *Journal of Innovation & Knowledge*, *15*, 101002. https://doi.org/10.1016/j.jik.2026.101002

Lukacs, E., Mallek, S., & Cheng, J. (2026). Generative AI-driven transition to circular and responsible supply chains: Unpacking the dynamics of eco-centric design intelligence and ethical responsiveness. *TECHNOLOGICAL FORECASTING AND SOCIAL CHANGE*, *225*. (rayyan-495755493). https://doi.org/10.1016/j.techfore.2025.124522

Maghroor, H. R., Madanchi, F., & O'Neal, T. (2025). Leveraging Generative AI for sustainable supply chain: Adoption challenges and strategic insights. *Production Planning & Control*, 1–20. https://doi.org/10.1080/09537287.2025.2561967

Mariani, M., & Dwivedi, Y. K. (2024). Generative artificial intelligence in innovation management: A preview of future research developments. *Journal of Business Research*, *175*, 114542. https://doi.org/10.1016/j.jbusres.2024.114542

Marzi, G., & Balzano, M. (2025). Artificial intelligence and the reconfiguration of NPD Teams: Adaptability and skill differentiation in sustainable product innovation. *Technovation*, *145*, 103254–103254. https://doi.org/10.1016/j.technovation.2025.103254

McDougall, N., Wagner, B., & MacBryde, J. (2022). Leveraging competitiveness from sustainable operations: Frameworks to understand the dynamic capabilities needed to realise NRBV supply chain strategies. *Supply Chain Management: An International Journal*, *27*(1), 12–29. https://doi.org/10.1108/SCM-11-2018-0393

Naz, F., Agrawal, R., Kumar, A., Gunasekaran, A., Majumdar, A., & Luthra, S. (2022). Reviewing the applications of artificial intelligence in sustainable supply chains: Exploring research propositions for future directions. *Business Strategy and the Environment*, *31*(5), 2400–2423. https://doi.org/10.1002/bse.3034

Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., Akl, E. A., Brennan, S. E., Chou, R., Glanville, J., Grimshaw, J. M., Hróbjartsson, A., Lalu, M. M., Li, T., Loder, E. W., Mayo-Wilson, E., McDonald, S., … Moher, D. (2021). The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *BMJ*, n71. https://doi.org/10.1136/bmj.n71

Qiao, R., & Zhao, L. (2025). Does supply chain digitalisation reduce supply chain financing risks? Dual mechanisms by integrating logistics, information flow and capital flow. *International Journal of Logistics Research and Applications*, 1–22. https://doi.org/10.1080/13675567.2025.2571694

Qin, F., & Zhang, M. (2026). AI-driven green transformation: A LLM-based AI quantification and empirical evidence from China. *International Review of Financial Analysis*, *109*, 104790. https://doi.org/10.1016/j.irfa.2025.104790

Riad, M., Naimi, M., & Okar, C. (2024). Enhancing Supply Chain Resilience Through Artificial Intelligence: Developing a Comprehensive Conceptual Framework for AI Implementation and Supply Chain Optimization. *Logistics*, *8*(4), 111. https://doi.org/10.3390/logistics8040111

Shabbir, M., & Keshtiban, A. (2026). Generative Artificial Intelligence and Social Entrepreneurship: Rethinking Collaborative Ecosystem Innovation for Sustainable Development. *Business Strategy and the Environment*. https://doi.org/10.1002/bse.70742

Sabina-Cristiana Necula, & Rieder, E. (2025). Generative and Adaptive AI for Sustainable Supply Chain Design. *Journal of Theoretical and Applied Electronic Commerce Research*, *20*(3), 240–240. https://doi.org/10.3390/jtaer20030240

Seuring, S., & Müller, M. (2008). From a literature review to a conceptual framework for sustainable supply chain management. *Journal of Cleaner Production*, *16*(15), 1699–1710. https://doi.org/10.1016/j.jclepro.2008.04.020

Singh, A., Alghafes, R., Koltai, J. P., & Vishnoi, S. K. (2026). Harnessing Generative AI for Sustainable Supply Chains: Lean, Circular and Green Perspectives. *Business Strategy and the Environment*, bse.70515. https://doi.org/10.1002/bse.70515

Sodhi, M. S., & Tang, C. S. (2021). Supply Chain Management for Extreme Conditions: Research Opportunities. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3861194

Sonar, H., Ghag, N., & Sharma, I. (2026). Bridging theory and practice in AI-driven supply chains: Prioritizing LLM adoption challenges and SCOR-based applications.

International Journal of Production Economics, *296*. Scopus. https://doi.org/10.1016/j.ijpe.2026.110008

Stroumpoulis, A., & Kopanaki, E. (2022). Theoretical Perspectives on Sustainable Supply Chain Management and Digital Transformation: A Literature Review and a Conceptual Framework. *Sustainability*, *14*(8), 4862. https://doi.org/10.3390/su14084862

Teece, D. J. (2007). Explicating dynamic capabilities: The nature and microfoundations of (sustainable) enterprise performance. *Strategic Management Journal*, *28*(13), 1319–1350. https://doi.org/10.1002/smj.640

Teece, D. J. (2025). The multinational enterprise, capabilities, and digitalization: Governance and growth with world disorder. *Journal of International Business Studies*, *56*(1), 7–22. https://doi.org/10.1057/s41267-024-00767-7

Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic Capabilities and Strategic Management. *Strategic Management Journal*, *18*(7), 509–533. https://www.jstor.org/stable/3088148

Tranfield, D., Denyer, D., & Smart, P. (2003). Towards a Methodology for Developing Evidence-Informed Management Knowledge by Means of Systematic Review. *British Journal of Management*, *14*(3), 207–222. https://doi.org/10.1111/1467-8551.00375

Wamba, S. F., Queiroz, M. M., Guthrie, C., & Braganza, A. (2021). Industry experiences of artificial intelligence (AI): benefits and challenges in operations and supply chain management. *Production Planning & Control*, *33*(16), 1–13. https://doi.org/10.1080/09537287.2021.1882695

Wu, H., Liu, J., & Liang, B. (2024). AI-Driven Supply Chain Transformation in Industry 5.0: Enhancing Resilience and Sustainability. *Journal of the Knowledge Economy*, *16*(1), 3826–3868. https://doi.org/10.1007/s13132-024-01999-6

Yang, Z., Guo, X., Sun, J., Zhang, Y., & Wang, Y. (2024). What Does Not Kill You Makes You Stronger: Supply Chain Resilience and Corporate Sustainability Through Emerging IT Capability. *IEEE Transactions on Engineering Management*, *71*, 10507–10521. https://doi.org/10.1109/TEM.2022.3209613

Zahra, S. A., Petricevic, O., & Luo, Y. (2022). Toward an action-based view of dynamic capabilities for international business. *Journal of International Business Studies*, *53*(4), 583–600. https://doi.org/10.1057/s41267-021-00487-2

Appendices

Appendix 1. Characteristics and key Findings

s no.	Title	Authors	Year	Methodology	Sample Size	Context Country	Key Findings
1	A systematic analysis of generative artificial intelligence for supply chain transformation	Zied Bahroun, Afef Saihi, Rami As'ad, Moayad Tanash	2026	PRISMA-guided Systematic Literature Review (SLR)	98 peer-reviewed studies	Global	GAI serves as a new decision layer for scenario generation and textual insights. 80% of applications focus on Plan and Enable processes. LLM/GPT underpin 40% of implementations. Reported benefits include demand forecasting, risk analysis, and sustainability analytics.
2	AI-driven green transformation: A LLM-based AI quantification and empirical evidence from China	Fei Qin, Mao Zhang	2026	DMLDID (Two-way fixed-effects model with BERT-based textual index)	40,423 observations	China	AI significantly facilitates green transformation by easing financing constraints, strengthening knowledge absorption, and reducing environmental uncertainty. Spillover effects are stronger upstream.
3	AI-Driven Supply Chain Transformation in Industry 5.0: Enhancing Resilience and Sustainability	Haoyang Wu, Jing Liu, Biming Liang	2024	Performance Appraisal (PA), Bayesian Best-Worst Method (B-BWM), and Pareto analysis	40 specialists	China	Identified key strategies: IoT monitoring, circular production, and digital twins. IoT monitoring was found to be the most important factor (weight 0.1657).
4	AI-process integrative framework for driving deep digital supply chain transformation	Samia Chehbi Gamoura, David Damand, Youssef Lahrichi, Tarik Saikouk	2025	Design Science Research (DSR) and exploratory case studies	3 industrial cases	France, Morocco, USA	Revealed fragmented AI adoption, challenges with integration complexity, and deficient consideration of social implications.
5	Applications of artificial intelligence in closed-loop supply chains: Systematic literature review and future research agenda	Sourabh Bhattacharya, Kannan Govindan, Surajit Ghosh Dastidar, Preeti Sharma	2024	Systematic Literature Review (SLR) and Bibliometric Analysis	303 peer-reviewed articles	Global	Identified top 10 AI techniques (GA, SI, SA, RF, RL, KMCA, ANN, DNN, FL, SIM). GA is the most widely applied. Established a research framework for future AI applications in CLSC.

6	Artificial intelligence and the reconfiguration of NPD Teams	Giacomo Marzi, Marco Balzano	2025	Multi-industry survey and Multiple regression analysis	331 NPD teams	Not specific	Team adaptability affects sustainable product innovation (SPI). GenAI use strengthens these relationships by augmenting knowledge recombination.
7	Artificial intelligence in operations management and supply chain management: an exploratory case study	Petri Helo, Yuqiuge Hao	2022	Exploratory case studies and semi-structured interviews	4 international companies	Finland	AI creates value through reduced decision time, higher capacity utilization, and process automation in sales, production, and maintenance.
8	Bridging theory and practice in AI-driven supply chains: Prioritizing LLM adoption challenges	Harshad Sonar, Nikhil Ghag, Isha Sharma	2026	Delphi study and COCOSO method	12 industry experts	India	Identified output interpretability and over-reliance as critical barriers. Interpretability and human-AI interaction outweigh data-related concerns.
9	ChatGPT and generative artificial intelligence: an exploratory study of key benefits and challenges in operations and supply chain management	Samuel Fosso Wamba, Cameron Guthrie, Maciel M. Queiroz, Stefan Minner	2024	Exploratory descriptive study (Bi-gram, co-word network, and cluster analysis)	300 survey responses	USA and UK	Projects focus on operational gains like process efficiency and cost minimization. Key challenges include data quality, privacy, and organizational resistance. Identified six industry clusters based on adoption maturity.
10	Does generative AI affect firm sustainability and market performance?	Yatish Joshi, Intesar Almugren, Vikram Kumar Sharma, Gabriella Imre	2026	Mixed-methods design (Qualitative interviews + PLS-SEM)	385 respondents	India	Digital transformation and marketing capabilities enhance adoption. Regulatory support moderates the impact on sustainability.
11	Enhancing Supply Chain Resilience Through Artificial Intelligence	Meriem Riad, Mohamed Naimi, Chafik Okar	2024	Mixed-methods design (Interviews and performance analysis)	20 senior managers	Morocco	AI-driven automation and robotics improved efficiency and reduced errors. Success is tied to human factors like training and scenario planning.
12	Exploring the role of generative AI to enhance knowledge management capabilities for improved supply chain resilience in large-scale initiatives	Quba Ahmed, Muhammad Saleem Sumbal, Carman K. M. Lee	2025	Qualitative approach (Semi-structured interviews) and document reviews	23 elite workers	China and Pakistan	GenAI tools improve knowledge sharing and creation, enhancing decision-making in megaprojects. Trust and organizational culture are key moderators.
13	From Prompts to Performance: How Generative AI is Reshaping Supply Chain Flexibility	Surajit Bag	2025	Survey-based quantitative research (PLS-SEM)	600 samples	India	GenAI-enabled capabilities develop flexible supply chain capabilities. Organizational politics dampens these benefits.
14	Generative AI capabilities for green supply chain management improvement	Taufik Kurrahman, Feng Ming Tsai, Ming K. Lim, Kanchana Sethanan, Ming-Lang Tseng	2025	Integrated fuzzy Delphi (FDM) and FSE-DEMATEL	30 experts	Indonesia	Dynamic knowledge, innovative learning, reflexive control, and co-evolution are key capabilities. Predictive maintenance data is a practical priority.

15	Generative AI usage and sustainable supply chain performance	Lixu Li, Wenwen Zhu, Lujie Chen, Yaoqi Liu	2024	Practice-based view (PBV) and Survey analysis	213 manufacturing firms	China	GAI usage positively affects sustainable performance (SSCP), with green collaboration and circular economy implementation as mediators.
16	Generative AI, digital dexterity, and organizational future performance	David Yulong Liu, Muhammad Mustafa Kamal, Junpeng Dou, Justin Zuopeng Zhang	2026	PLS-SEM (Partial Least Squares Structural Equation Modeling)	296 firms	China	GenAI-enabled digital dexterity enhances decision-making quality. Ethical identity amplifies these effects, while regulatory governance strengthens the link to performance.
17	Generative AI, ESG Sensemaking, and Environmental Performance: an OIPT Perspective	Surajit Bag, Gautam Srivastava, Susmi Routray, Andrea Chiarini	2026	PLS-SEM and case triangulation	610 firms	India	GenAI integration enhances environmental performance directly and via ESG sensemaking. Sustainability information overload weakens this effect.
18	Generative AI-Driven resilience in supply chain management: UNISONE framework for disruption modelling and capacity optimisation	Kuo-Yi Lin, Shih-Yu Wu, Kotomichi Matsuno	2025	GAI-driven resilience framework (UNISONE) with Markov modelling and MIP	Data from 3 global regions	Not in source	Sustains service continuity above 90%, reduces cost volatility by nearly 20%, and accelerates recovery across disruption cycles.
19	Generative AI-driven transition to circular and responsible supply chains	Eszter Lukács, Sabrine Mallek, Jiyang Cheng	2026	Serial mediation model via Structural Equation Modeling (SmartPLS 4)	264 professionals	USA	Eco-design intelligence and predictive planning enhance sustainable reconfiguration capability, driving resilience. Regenerative policy ambidexterity acts as a negative moderator.
20	Generative and Adaptive AI for Sustainable Supply Chain Design	Sabina-Cristiana Necula, Emanuel Rieder	2025	Hybrid AI framework (VAE, NSGA-II, and DQN)	M5 Forecasting Dataset	USA and Romania	Pareto-optimal sourcing achieved 50% emission reductions for 10–15% cost increases. RL policy achieved an additional 10% emission reduction via adaptive transport modes.
21	Generative AI: Opportunities, Challenges, and Research Directions	Tonya Boone, Behnam Fahimnia, Ram Ganeshan, David M. Herold, and Nada R. Sanders	2025	Conceptual/Expert Panel	Multi-expert Commentary	Global	Comprehensive overview of GenAI opportunities and challenges. Identifies research priorities across disciplines. SCM applications noted as emerging area.
22	Generative artificial intelligence in supply chain and operations management: a capability-based framework for analysis and implementation	Ilya Jackson, Dmitry Ivanov, Alexandre Dolgui, Jafar Namdar	2024	Capability-based conceptual framework (Resource-Based View)	13 decision-making areas	Global	Defined core AI capabilities as learning, perception, prediction, interaction, adaptation, and reasoning. Introduced 'Creativity' as a new GAI capability. GAI shifts AI from automating rules to co-creating decision paths.

23	Generative artificial intelligence–driven sustainable supply chain management: a UNISONE framework for smart logistics and predictive analytics under Industry 5.0	Kuo-Yi Lin	2025	UNISONE framework (Multi-criteria reasoning and adaptive learning)	1 industrial case study	Taiwan	Improved delivery responsiveness, carbon efficiency, and sourcing stability. Hybrid scenarios showed the highest stakeholder alignment (86.4 score).
24	Generative Artificial Intelligence and Social Entrepreneurship: Rethinking Collaborative Innovation	Muhammad Salman Shabbir, Amir Keshtiban .	2026	Bibliometric mapping and systematic literature review	69	Global	Four thematic streams were identified. GenAI as ecosystem-level enabler. Ethical governance and sustainability transitions are emphasized. Framework for GenAI-social entrepreneurship developed.
25	Harnessing Generative AI for Sustainable Supply Chains: Lean, Circular and Green Perspectives	Ashutosh Singh, Rsha Alghafes, Judit Petra Koltai, Sushant Kumar Vishnoi	2026	Word2Vec modeling and Sentiment analysis	72 platforms; 35,449 reviews	Not specific	Lean themes are the most prominent in user language (sentiment 0.77), followed by green (0.75) and circular (0.64).
26	How can generative artificial intelligence empower circular supply chain practices?	Yutian Liu, Hong Tian	2026	Survey-based research using PLS-SEM	371 firms	China	GenAI positively affects circular practices through a mechanism of generative capability and iterative innovation.
27	How does supply chain digitalisation affect corporate green total factor productivity? The roles of dynamic capabilities and ChatGPT	Xuena Gao, Xiaoling Wang, Kanchana Sethanan	2026	DMLDID (Double machine learning for difference-in-differences)	24,072 observations	China	Digitalisation promotes GTFP through dynamic innovative, absorptive, and adaptive capabilities. ChatGPT use reinforces this positive effect.
28	How generative AI adoption affects supply chain resilience	Jiguang Guo, Fu Jia, Lujie Chen	2026	Fixed-effects regression and 2SLS on panel data	1,448 firm-year observations	China	Generative AI enhances resilience, especially in high-tech firms. Operational efficiency moderates this effect positively, while customer/supplier concentration moderates negatively.
29	Human-Centric Generative AI in Circular Supply Chains: Theoretical Insights From Ethics, Dynamic Capabilities, and Resource Conservation	Surajit Bag, Muhammad Sabbir Rahman, Susmi Routray, V. Raja Sreedharan	2025	Covariance-based structural equation modeling (CB-SEM)	2,000 responses (1,000 firms)	India and South Africa	Responsible GenAI use enhances circular supply chain performance (CSP) through AI-augmented supplier development (AISD). Effects are moderated by polycrisis experience.
30	Industry Experiences of Artificial Intelligence: Benefits and Challenges	Samuel Fosso Wamba, Maciel M. Queiroz, Cameron Guthrie, and Ashley Braganza	2025	Editorial introduction summarizing papers accepted for a special issue	8	Global	Identifies key benefits (efficiency, decision support) and challenges (data quality, skills gap) of AI implementation. Organizational readiness critical for success.

31	Integrating third-party logistics (3PL), forecast accuracy and emission management in triadic supply chains – a large language model-based approach	Mariusz Kmiecik	2026	LLM analysis (Gemini) for anomaly detection	22 triads	Poland	LLM successfully identified hidden inefficiencies and suggested structural transformations (e.g., shifting to concentrated triads) validated by experts.
32	Intelligence by design: Large language model work integration as strategic enablers for supply chain regeneration through digital and cognitive capabilities	Weiming Liu, Varun Chotia, Lu Wang, Prashant Sharma, Norah Albishri, Snigdha Dash	2026	PLS-SEM (Partial Least Squares Structural Equation Modeling)	281 respondents	USA and UK	LLM integration enhances regenerative capacity via digital process transformation and cognitive capability. Digital culture and AI governance are critical moderators.
33	Leveraging Generative AI for sustainable supply chain: adoption challenges and strategic insights	Hamid Reza Maghroor, Faraz Madanchi, Thomas O'Neal	2025	TOEH framework and DEMATEL	11 expert panels	North America and Europe	Human-centric barriers (resistance, skills) are rooted in technological readiness. Ethical concerns and data governance are primary causal factors.
34	Supply Chain Management in the Era of Generative AI (ChatGPT): Technology Fit and Drivers	Javed Aslam, Aqeela Saleem, Kee-Hung Lai	2025	PLS-SEM (Partial Least Squares Structural Equation Modeling)	382 professionals	Not specific	Task-Technology Fit enhances trust and satisfaction; technology anxiety acts as a significant barrier to adoption.
35	Understanding determinants of GenAI usage and its effect on SCM performance	Hemlata Gangwar, Mohammad Shameem, Sandeep Patel, Alex Koohang, Anuj Sharma	2025	Quantitative study using PLS-SEM	315 expert respondents	India	Performance expectancy, output quality, and management commitment drive usage, improving transparency and decision-making.

Appendix 2. Quality Assessment score card

S no.	File / Short Title	Authors	Q1 Clear Objectives (0–3)	Q2 Theoretical Grounding (0–3)	Q3 Methodology Rigor (0–3)	Q4 Validity of Findings (0–3)	Q5 Contribution (0–3)	Q6 IB Relevance (0–3)	Total (0–18)
1	A Systematic Analysis of Generative AI for Supply Chain Transformation	Bahroun, Saihi, As'ad & Tanash	3	2	3	3	3	2	**16**
2	AI and the Reconfiguration of NPD Teams: Adaptability and Skill Differentiation	Marzi & Balzano	3	3	3	3	3	1	**16**

3	AI in Operations Management and Supply Chain Management: Exploratory Case Study	Helo & Hao	2	1	2	2	2	3	**12**
4	AI-Driven Green Transformation: LLM-Based Quantification	Qin & Zhang	3	2	3	3	3	2	**16**
5	AI-Driven Supply Chain Transformation in Industry 5.0	Wu, Liu & Liang	2	2	3	2	2	3	**14**
6	AI-Process Integrative Framework for Deep Digital SC Transformation	Chehbi Gamoura, Damand, Lahrichi & Saikouk	2	2	2	2	2	2	**12**
7	Applications of AI in Closed-Loop Supply Chains: SLR	Bhattacharya, Govindan, Ghosh Dastidar & Sharma	3	2	3	3	3	2	**16**
8	Bridging Theory and Practice in AI-Driven Supply Chains: LLM Adoption Challenges	Sonar, Ghag & Sharma	3	3	3	3	3	2	**17**
9	ChatGPT and GenAI: Exploratory Study of Benefits and Challenges in OSCM	Fosso Wamba, Guthrie, Queiroz & Minner	3	2	3	3	3	3	**17**
10	Does Generative AI Affect Firm Sustainability and Market Performance?	Joshi, Almugren, Sharma & Imre	3	3	3	3	3	3	**18**
11	Enhancing Supply Chain Resilience Through AI: Conceptual Framework	Riad, Naimi & Okar	3	1	2	2	2	2	**12**
12	Exploring GenAI to Enhance Knowledge Management for Supply Chain Resilience	Ahmed, Sumbal & Lee	3	3	3	3	3	3	**18**
13	From Prompts to Performance: How GenAI is Reshaping Supply Chain Flexibility	Bag	3	3	3	3	3	2	**17**
14	GAI-Driven SSCM: UNISONE Framework for Smart Logistics under Industry 5.0	Lin	3	2	2	2	3	2	**14**
15	GenAI and Social Entrepreneurship: Rethinking Collaborative Ecosystem Innovation	Shabbir & Keshtiban	3	3	3	3	3	3	**18**

16	GenAI in Supply Chain and Operations Management: Capability-Based Framework	Jackson, Ivanov, Dolgui & Namdar	3	3	2	2	3	3	**16**
17	GenAI, Digital Dexterity, and Organizational Future Performance for Sustainable SC	Liu, Kamal, Dou & Zhang	3	3	3	3	3	2	**17**
18	GenAI-Driven Resilience in SCM: UNISONE Framework for Disruption Modelling	Lin, Wu & Matsuno	3	2	3	3	3	3	**17**
19	GenAI-Driven Transition to Circular and Responsible Supply Chains	Lukacs, Mallek & Cheng	3	2	3	3	3	2	**16**
20	Generative AI Capabilities for GSCM Improvement: Extended DCV	Kurrahman, Tsai, Lim, Sethanan & Tseng	3	3	3	2	3	2	**16**
21	Generative AI Usage and Sustainable Supply Chain Performance: Practice-Based View	Li, Zhu, Chen & Liu	3	3	3	3	3	2	**17**
22	Generative AI, ESG Sensemaking, and Environmental Performance: OIPT Perspective	Bag, Srivastava, Routray & Chiarini	3	3	3	3	3	2	**17**
23	Generative AI: Opportunities, Challenges, and Research Directions for SC Resilience	Boone, Fahimnia, Ganeshan, Herold & Sanders	3	2	1	2	3	3	**14**
24	Generative and Adaptive AI for Sustainable Supply Chain Design	Necula & Rieder	3	1	3	2	3	1	**13**
25	Harnessing GenAI for Sustainable Supply Chains: Lean, Circular and Green Perspectives	Singh, Alghafes, Koltai & Vishnoi	3	2	3	2	2	2	**14**
26	How Can GenAI Empower Circular Supply Chain Practices? Evidence from China	Liu & Tian	3	3	3	3	3	2	**17**
27	How GenAI Adoption Affects Supply Chain Resilience: OSCM Perspective	Guo, Jia & Chen	3	3	3	3	3	2	**17**
28	How SC Digitalisation Affects Corporate Green Total Factor Productivity: DC and ChatGPT	Gao, Wang & Sethanan	3	3	3	3	3	2	**17**

29	Human-Centric GenAI in Circular Supply Chains: Ethics, DC, and Resource Conservation	Bag, Rahman, Routray & Sreedharan	3	3	3	3	3	3	**18**
30	Industry Experiences of AI: Benefits and Challenges in OSCM (Editorial)	Fosso Wamba, Queiroz, Guthrie & Braganza	1	1	1	1	2	2	**8**
31	Integrating 3PL, Forecast Accuracy and Emission Management: LLM-Based Approach	Kmiecik	3	3	3	2	3	2	**16**
32	Intelligence by Design: LLM Work Integration as Strategic Enablers for SC Regeneration	Liu, Chotia, Wang, Sharma, Albishri & Dash	3	3	3	3	3	2	**17**
33	Leveraging GenAI for Sustainable Supply Chain: Adoption Challenges and Strategic Insights	Maghroor, Madanchi & O'Neal	3	2	3	2	3	2	**15**
34	Supply Chain Management in the Era of Generative AI (ChatGPT): TTF and Psychological Drivers	Aslam, Saleem & Lai	3	3	3	3	3	2	**17**
35	Understanding Determinants of GenAI Usage and Its Effect on SCM Performance: DCV	Gangwar, Shameem, Patel, Koohang & Sharma	3	3	3	3	3	2	**17**