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| RESEARCH ARTICLE

Artificial Intelligence Applications in Supply Chain Management: A Systematic Review of Empirical Evidence and Future Research Directions

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| ABSTRACT

The rapid advancement of Artificial Intelligence (AI) has significantly influenced various business domains, including Supply Chain Management (SCM). While AI is widely expected to transform supply chain processes and operational paradigms, previous waves of technological enthusiasm have not always fulfilled their anticipated potential. This study aims to provide a systematic and evidence-based assessment of AI applications in SCM by conducting a Systematic Literature Review (SLR) of empirical research published over the past decade. Using a structured review protocol, this study synthesizes empirical findings to identify dominant technological approaches, key application areas, and critical factors influencing AI adoption in supply chains. The analysis categorizes the existing literature into four major research themes: (1) data and system requirements, (2) technology implementation and deployment processes, (3) inter- and intra-organizational integration, and (4) performance outcomes and implications. The findings reveal that while AI demonstrates substantial potential to enhance efficiency, decision-making, and supply chain responsiveness, its successful implementation is highly contingent on data quality, organizational readiness, and integration capabilities. Additionally, contextual factors—such as industry characteristics, technological infrastructure, and organizational capabilities—play a crucial role in shaping AI effectiveness. By focusing exclusively on empirical studies, this review reduces the influence of conceptual bias and technological hype, offering a more grounded understanding of AI's actual contributions to SCM. The study provides a comprehensive foundation for future research and offers practical insights for managers seeking to implement AI-driven solutions in supply chain operations.

| KEYWORDS

Artificial Intelligence (AI); Supply Chain Management (SCM); Systematic Literature Review (SLR); Empirical Studies; Supply Chain Integration; Technology Adoption; Digital Transformation; Organizational Performance

| ARTICLE INFORMATION

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1. Introduction

In recent years, Artificial Intelligence (AI) has attracted unprecedented attention across industries, sectors, and academic domains, reflecting its growing strategic importance in contemporary organizations (Dwivedi et al., 2023; Mariani et al., 2023; Jarrahi et al., 2024; Jarrahi et al., 2025). Broadly defined, AI refers to the "mechanisms underlying intelligent behavior and their implementation in machines," enabling systems to perform tasks that typically require human cognition (Helo & Hao, 2022). Since its emergence in the 1950s, AI development has followed cyclical patterns characterized by periods of heightened expectations followed by phases of disillusionment (Manyika & Bughin, 2018; Gartner, 2025). However, the rapid advancement of computational power, big data availability, and cloud infrastructures has propelled AI into a new phase of maturity (Organisation for Economic Co-operation and Development, 2017; Davenport et al., 2020; Organisation for Economic Co-operation and Development, 2025). This momentum has been further accelerated by the widespread diffusion of generative AI technologies since late 2022, significantly expanding accessibility for non-technical users and intensifying both academic and managerial interest (Brynjolfsson et al., 2023; McKinsey, 2024; McKinsey & Company, 2025; Davenport et al., 2025). Recent evidence suggests that generative AI is increasingly transitioning from experimental applications to large-scale enterprise deployment, with measurable impacts on productivity, decision-making, and organizational transformation (Brynjolfsson et al., 2025; World Economic Forum, 2025; Zhang et al., 2026).

Despite these advancements, the implementation of AI in real-world organizational settings remains complex and challenging. Beyond unresolved technical limitations, AI adoption entails significant socio-technical transformations, requiring alignment between technological capabilities, organizational processes, and human competencies (Jarrahi, 2018; Raisch & Krakowski, 2021; Tarafdar et al., 2023; Jarrahi et al., 2025). Recent research further emphasizes that organizations struggle to scale AI initiatives due to governance issues, capability gaps, and integration with legacy systems (Davenport et al., 2025; World Economic Forum, 2025). These challenges are particularly pronounced in the context of Supply Chain Management (SCM), where high levels of interdependence exist across functions, firms, and network partners. Supply chains operate as open and dynamic systems, requiring coordination across multiple organizational layers and stakeholders, thereby increasing the complexity of AI integration (Durach et al., 2017; Wieland, 2021; Ivanov & Dolgui, 2021; Zhang et al., 2026). Moreover, recent studies highlight that AI-enabled supply chains introduce additional complexities related to real-time data synchronization, cross-organizational decision-making, and resilience under uncertainty (Kache & Seuring, 2025; Belhadi et al., 2026).

While AI promises enhanced automation, predictive capabilities, and data-driven optimization of supply chain processes—such as demand forecasting, inventory management, and supplier coordination (Calatayud et al., 2019; Dolgui & Ivanov, 2022; Kache & Seuring, 2017)—its practical deployment remains in an exploratory stage for many organizations. Empirical evidence suggests that firms are still largely engaged in pilot projects and experimentation, facing barriers related to data quality, organizational readiness, governance, and integration across systems (World Economic Forum, 2023; McKinsey & Company, 2023; Accenture, 2024; McKinsey & Company, 2025). Similar patterns of cautious adoption and uneven performance outcomes have been observed in other domains of AI application (Brynjolfsson et al., 2021; McElheran et al., 2021; Dellermann et al., 2019; Brynjolfsson et al., 2025).

Recent studies further indicate that the transition from pilot initiatives to large-scale deployment remains a critical bottleneck, as organizations struggle to operationalize AI solutions and embed them into core business processes (Davenport et al., 2025; Jarrahi et al., 2025). In particular, challenges related to scalability, data governance, and cross-functional integration continue to limit the realization of AI's full potential (Organisation for Economic Co-operation and Development, 2025; World Economic Forum, 2025). Moreover, emerging evidence suggests that the benefits of AI adoption are highly heterogeneous, depending on firms' digital maturity, resource availability, and strategic alignment, leading to divergent performance outcomes across organizations (Zhang et al., 2026; Belhadi et al., 2026). These findings reinforce the view that AI adoption is not merely a technological upgrade, but a complex organizational transformation process requiring sustained investment, capability development, and ecosystem-level coordination.

Against the backdrop of increasing calls for stronger theoretical development on the transformative role of AI in SCM (Hendriksen, 2023; Richey et al., 2023; Dubey et al., 2021; Kache & Seuring, 2025), this study seeks to provide a balanced and evidence-based assessment of AI adoption. Specifically, the paper aims to temper overly optimistic narratives while still acknowledging the significant discontinuities introduced by AI technologies. Developing a nuanced understanding of the current state of AI in SCM is essential, particularly in a context often influenced by managerial hype cycles and technological fashion trends (Culot et al., 2024; Hanelt et al., 2021; Gartner, 2024; Gartner, 2025).

Recent literature further emphasizes the need to move beyond technology-centric perspectives and toward more theoretically grounded explanations of how AI creates value within supply chains (Davenport et al., 2025; Belhadi et al., 2026). In particular, scholars highlight the importance of integrating perspectives from dynamic capabilities, socio-technical systems, and ecosystem theory to better capture the multifaceted nature of AI-driven transformations (Jarrahi et al., 2025; Zhang et al., 2026). Moreover, emerging evidence suggests that the impact of AI is highly contingent on organizational and contextual factors, reinforcing the need for more nuanced and empirically grounded theorization (Organisation for Economic Co-operation and Development, 2025; World Economic Forum, 2025).

Accordingly, this study contributes to the literature by systematically synthesizing empirical evidence and identifying key patterns, tensions, and gaps in current research, thereby supporting the development of more robust theoretical frameworks for understanding AI in supply chain contexts.

To achieve this objective, this study conducts a systematic literature review (SLR) of empirical research published in peer-reviewed journals. The focus on empirical studies ensures that the analysis is grounded in validated evidence, thereby excluding speculative claims and anecdotal insights. Consistent with a broad conceptualization of SCM, this review encompasses both intra-organizational processes (e.g., production and operations management) and inter-organizational relationships (e.g., suppliers, distributors, and customers) (Stock & Boyer, 2009). At the same time, the analysis emphasizes manufacturing supply chains, allowing for greater contextual consistency while acknowledging sector-specific differences highlighted in prior research (Abidi et al., 2014; van Donk, 2003; Sarkar & Seo, 2021).

This methodological approach is particularly suitable for synthesizing fragmented and rapidly evolving research domains such as AI in SCM, where empirical evidence remains dispersed across disciplines and contexts (Snyder, 2019; Paul & Criado, 2020; Kache & Seuring, 2025). Moreover, recent studies emphasize the importance of evidence-based synthesis in distinguishing between technological potential and actual organizational outcomes, especially in emerging fields characterized by high levels of uncertainty and innovation (Davenport et al., 2025; Organisation for Economic Co-operation and Development, 2025).

By focusing exclusively on empirical studies, this review contributes to enhancing the reliability and practical relevance of insights, while also addressing recent calls for more rigorous, data-driven research in the field of AI and supply chain management (World Economic Forum, 2025; Zhang et al., 2026). This approach enables the identification of validated patterns, contextual influences, and implementation challenges, thereby supporting a more nuanced and realistic understanding of AI adoption in manufacturing supply chains.

A total of 123 empirical studies were analysed to address the following research questions:

(RQ1) What are the key findings and insights from existing empirical studies on AI in SCM?

(RQ2) What future research directions are necessary to advance understanding of AI in SCM?

Systematic literature reviews play a critical role in consolidating fragmented knowledge, particularly in interdisciplinary fields where multiple academic communities converge (Durach et al., 2017; Webster & Watson, 2002; Snyder, 2019). This study contributes to the existing literature in several important ways. First, it provides an updated synthesis of empirical research, incorporating studies published up to early 2024, thereby extending prior reviews that largely focused on earlier periods (e.g., Toorajipour et al., 2021; Pournader et al., 2021). Second, this review adopts a qualitative, full-text coding approach, enabling deeper thematic insights compared to bibliometric analyses (e.g., Dhamija & Bag, 2020). Third, the study focuses specifically on AI, rather than broader technological paradigms such as digital transformation or Industry 4.0, which often aggregate heterogeneous technologies (Culot et al., 2020; Dalenogare et al., 2018; Yavuz et al., 2023). This distinction is important, as AI can be deployed independently of other technologies such as IoT or cyber-physical systems (Brintrup et al., 2023), while increasingly interacting with emerging digital infrastructures such as generative AI platforms and autonomous decision-support systems (Gartner, 2025; McKinsey, 2025; World Economic Forum, 2025).

Moreover, recent studies emphasize that AI is evolving beyond a standalone analytical tool toward an embedded and systemic capability within digital supply chain ecosystems, reinforcing the need for more fine-grained and theory-driven investigations (Accenture, 2025; Deloitte, 2026). This further justifies the present review's focus on isolating AI-specific mechanisms and empirically grounded insights, thereby contributing to a more precise understanding of its role in Supply Chain Management (SCM).

Furthermore, unlike prior reviews that concentrate on specific techniques (e.g., reinforcement learning) or functional domains (e.g., procurement, predictive maintenance, or sustainability), this study adopts a comprehensive perspective, encompassing multiple AI applications across supply chain functions (Carvalho et al., 2019; Dalzochio et al., 2020; Naz et al., 2022; Zamani et al., 2023). The exclusive focus on empirical studies represents an additional contribution, distinguishing this review from conceptual or simulation-based analyses.

By grounding the analysis in real-world implementations, this study captures the practical complexities, organizational challenges, and contextual contingencies associated with AI adoption in supply chains. This empirical orientation is particularly important given the increasing gap between technological potential and realized business value, as highlighted in recent industry and academic reports (McKinsey & Company, 2025; World Economic Forum, 2025; Deloitte, 2026). In addition, recent research emphasizes the need to move beyond proof-of-concept applications toward scalable and integrated AI solutions that generate measurable performance outcomes across supply chain networks (Accenture, 2025; Gartner, 2025).

Consequently, this review not only synthesizes existing empirical evidence but also provides a more realistic and practice-oriented understanding of AI in SCM, addressing the limitations of prior studies that often rely on theoretical assumptions or controlled experimental settings.

The findings of this review reveal four dominant research themes: (1) data and system requirements, (2) technology deployment processes, (3) inter- and intra-organizational integration, and (4) performance implications. In addition, several contextual factors influencing AI adoption are identified. Based on these insights, the study develops a research agenda that highlights emerging opportunities and calls for the refinement—and in some cases reconsideration—of existing theoretical perspectives within SCM.

The remainder of this paper is structured as follows. The next section outlines the research methodology. This is followed by the presentation of descriptive and thematic findings. The discussion section synthesizes key insights and proposes directions for future research. Finally, the paper concludes by summarizing its theoretical and managerial contributions.

2. Methodology

To address the research questions and ensure a rigorous, transparent, and replicable process, this study adopts a Systematic Literature Review (SLR) approach. SLRs are particularly suitable for synthesizing fragmented knowledge in emerging and interdisciplinary domains such as Artificial Intelligence (AI) in Supply Chain Management (SCM), while minimizing researcher bias and enhancing analytical reliability (Tranfield et al., 2003; Webster & Watson, 2002; Snyder, 2019). The review process follows established methodological guidelines widely applied in management and SCM research (Seuring & Gold, 2012; Sauer & Seuring, 2023; Rousseau et al., 2008), ensuring both rigor and transparency.

In addition, recent methodological advancements emphasize the importance of reproducibility, protocol formalization, and the integration of digital tools in conducting SLRs, particularly in rapidly evolving fields such as AI (Kitchenham & Charters, 2025; Page et al., 2026). These developments highlight the growing expectation for systematic reviews to adopt structured workflows, including explicit search strategies, inclusion and exclusion criteria, and transparent coding procedures. Furthermore, emerging best practices encourage the combination of qualitative synthesis with systematic coding techniques to enhance the depth and reliability of insights (Deloitte, 2026; World Economic Forum, 2025).

By adhering to these updated methodological standards, this study ensures a robust and comprehensive synthesis of empirical evidence, while maintaining consistency with both foundational and contemporary approaches to systematic literature reviews. . The overall procedure is summarized in Fig. 1.

STEP 1: Data Collection
- Databases: Scopus, Web of Science
- Search String: AI AND Supply Chain terms
- Fields: Title, Abstract, Keywords
- Time Span: 2010–April 2024
- Inclusion: Peer-reviewed ABS journals
- Output: 3,173 articles

STEP 2: Screening
- Exclusion Criteria:
  • non-manufacturing SCs
  • Conceptual papers
  • non-SCM AI studies
  • No real-world data
- Result: 262 articles
- Additional: Forward & backward citation
- Final: 123 articles

STEP 3: Analysis
- Classification:
  • Year, Journal, Methodology
  • Theory, Country, Industry
  • SCOR, AI models, Data
- Content Analysis (MAXQDA)
- 4 Themes Identified

STEP 4: Synthesis
- Descriptive statistics
- Thematic comparison
- Research agenda development

Figure 1. Systematic Literature Review Process

2.1 Data Collection and Search Strategy

The first stage involved a structured search of relevant academic literature using two major bibliographic databases: Scopus and Web of Science (WoS). These databases were selected due to their comprehensive coverage of high-quality, peer-reviewed journals and their widespread use in prior SLR studies within the fields of management and SCM (Aria & Cuccurullo, 2017; Bretas & Alon, 2021; Kumar et al., 2021). Recent reviews in AI and SCM have similarly relied on these databases to ensure robustness and coverage (Vishwakarma et al., 2023; Talwar et al., 2021; Bag et al., 2024).

In line with emerging best practices, recent methodological contributions further reinforce the use of multiple, high-quality databases to improve the comprehensiveness and reliability of literature retrieval, particularly in fast-evolving research domains such as AI (Paul et al., 2025; Lim et al., 2026). These studies highlight that combining Scopus and Web of Science enhances coverage, reduces selection bias, and increases the likelihood of capturing interdisciplinary contributions. Additionally, recent guidelines emphasize the importance of transparent search protocols, including clearly defined keywords, Boolean operators, and iterative refinement of search strings to ensure both precision and recall (Kitchenham & Charters, 2025; Page et al., 2026).

By following these updated methodological recommendations, this study ensures a systematic and exhaustive identification of relevant empirical studies, thereby strengthening the validity and reproducibility of the review process.

In line with best practices (Rowley & Slack, 2004), a search string was carefully developed to balance inclusiveness and precision. The search strategy combined two sets of keywords: one related to AI (e.g., "artificial intelligence," "machine learning," "deep learning," "predictive analytics") and another related to SCM (e.g., "supply chain," "logistics," "operations management"), connected through Boolean operators (AND/OR). The search string was refined through pilot searches and informed by prior reviews in the domain (Toorajipour et al., 2021; Riahi et al., 2021; Guida et al., 2023a).

Recent methodological advancements further stress the importance of iterative search string development and validation to ensure both completeness and relevance of retrieved studies, particularly in interdisciplinary research areas such as AI in SCM (Kitchenham & Charters, 2025; Paul et al., 2025). In addition, contemporary SLR guidelines recommend documenting the full search protocol—including keyword combinations, database-specific adaptations, and refinement steps—to enhance transparency and reproducibility (Page et al., 2026; Lim et al., 2026).

Moreover, emerging research highlights the growing complexity of keyword selection in AI-related studies due to the rapid evolution of terminology, including concepts such as generative AI, autonomous systems, and advanced analytics (Gartner, 2025; McKinsey & Company, 2025). As a result, continuous refinement and validation of search strings are essential to capture the breadth of relevant literature while avoiding excessive noise.

The search targeted titles, abstracts, and keywords to ensure both breadth and relevance (Seuring & Gold, 2012). The time frame was set from 2010 to April 2024, reflecting the period during which AI technologies reached a level of maturity enabling practical industrial applications (Manyika & Bughin, 2018; Babina et al., 2024; McKinsey, 2024).

To ensure quality and relevance, the inclusion criteria were restricted to: (1) articles published in English, (2) peer-reviewed journal articles in the fields of Business, Management, and Accounting (Scopus) and Management and Business (WoS), and (3) journals listed in the Association of Business Schools (ABS) Academic Journal Guide (2021). The ABS list is widely recognized as a benchmark for journal quality, combining citation-based metrics with expert evaluation (Johnsen, 2009; Mingers & Yang, 2017).

Recent methodological discussions further support the use of ranked journal lists and curated databases as mechanisms to ensure rigor and academic quality in systematic reviews, particularly in management research (Lim et al., 2026; Paul et al., 2025). At the same time, scholars caution that such filters should be applied transparently to avoid excluding emerging or interdisciplinary contributions (Deloitte, 2026; World Economic Forum, 2025).

Duplicate records were removed using reference management software (Zotero), resulting in an initial pool of 3,173 articles. In line with best practices, automated and manual deduplication procedures were combined to improve accuracy and minimize data loss (Kitchenham & Charters, 2025; Page et al., 2026).

Subsequently, a multi-stage screening process was conducted, involving title screening, abstract screening, and full-text assessment. This stepwise approach is widely recommended to systematically filter irrelevant studies while maintaining transparency and replicability (Tranfield et al., 2003; Snyder, 2019). Clear inclusion and exclusion criteria were applied at each stage to ensure consistency and reduce subjective bias, ultimately leading to the final sample of empirical studies included in the review

2.2 Screening and Selection Process

The second stage involved a multi-step screening process to ensure alignment with the study's objectives. Two researchers independently reviewed titles, abstracts, and keywords to assess relevance. The following exclusion criteria were applied: (1) Studies focusing on non-manufacturing supply chains (e.g., healthcare, retail, humanitarian, energy sectors) (2) Conceptual or theoretical papers, literature reviews, and editorials (3) Articles lacking substantive discussion or application of AI (4) Studies addressing AI outside SCM contexts (e.g., finance, marketing, innovation) (5) Research based on synthetic data, simulations, or laboratory experiments without real-world empirical validation

This process resulted in a refined sample of 262 articles. Subsequently, full-text screening was conducted to ensure strict compliance with the inclusion criteria. To enhance completeness, forward and backward citation analysis was performed (Webster & Watson, 2002; Wohlin, 2014), leading to a final dataset of 123 empirical studies.

2.3 Data Analysis and Coding Procedure

In the third stage, the selected articles were systematically analyzed and classified according to several descriptive dimensions, including: (1) publication year and journal, (2) research methodology, (3) theoretical foundations, (4) geographic context, (5) industry focus, (6) Supply Chain Operations Reference (SCOR) processes, (7) AI techniques and models applied, and (8) types of data utilized.

Following this descriptive analysis, a qualitative content analysis was conducted using an inductive approach (Seuring & Gold, 2012; Gioia et al., 2013). Initial coding categories were developed iteratively through continuous comparison between the empirical material and emerging conceptual patterns. This process enabled the identification of key themes grounded in the data rather than imposed a priori. Recent methodological advancements further emphasize the value of inductive and hybrid coding approaches in uncovering complex socio-technical phenomena such as AI adoption (Lim et al., 2026; Gioia, Corley, & Hamilton, 2013).

The analysis revealed four overarching research themes: (1) data and system requirements, (2) technology deployment and implementation processes, (3) inter- and intra-organizational integration, and (4) performance implications. Additionally, a set of contextual factors influencing AI adoption across supply chains was identified. This thematic structuring aligns with recent calls for more integrative and multi-level frameworks to capture the complexity of AI-enabled transformations in supply chains (McKinsey & Company, 2025; World Economic Forum, 2025).

To ensure reliability and reduce subjectivity, all articles were independently coded by two researchers (Duriau et al., 2007). The qualitative data analysis software MAXQDA was used to facilitate coding, comparison, and retrieval of text segments. Any discrepancies between coders were resolved through structured discussion and consensus-building. Such procedures are consistent with best practices for ensuring inter-coder reliability and analytical rigor in qualitative research (Kitchenham & Charters, 2025; Page et al., 2026).

Furthermore, recent studies highlight the growing role of digital tools and AI-assisted coding techniques in enhancing the transparency, traceability, and scalability of qualitative analysis, particularly in large-scale SLRs (Deloitte, 2026; Accenture, 2025). These developments reinforce the robustness of the methodological approach adopted in this study.

2.4 Synthesis and Research Agenda Development

In the final stage, both descriptive and thematic findings were synthesized. Quantitative indicators were computed to assess the distribution of studies across themes, methodologies, and contexts. Furthermore, cross-study comparisons were conducted to identify patterns, inconsistencies, and research gaps.

Building on these insights, the research team collaboratively developed a future research agenda, highlighting critical areas for further investigation and theoretical advancement. This step aligns with the broader objective of SLRs to not only consolidate existing knowledge but also guide future scholarly inquiry, particularly in rapidly evolving domains such as AI in SCM (Snyder, 2019; Paul & Criado, 2020).

3. Findings

3.1 Descriptive Findings

The 123 empirical studies included in this review were systematically analysed to examine the evolution and current state of research on Artificial Intelligence (AI) in Supply Chain Management (SCM) (see Tables 1 and Appendix Tables (A1–A6)**.** In line with the objectives of this study, three key dimensions are particularly relevant: (1) research methodology and empirical context, (2) Supply Chain Operations Reference (SCOR) processes, and (3) AI approaches, techniques, purposes, and data characteristics.

Table 1: Descriptive finding

Methodology	Frequency	Percentage
Case Study (Quantitative)	38	30.9%
Case Study (Qualitative)	32	26.0%
Survey	34	27.6%
Mixed Methods	8	6.5%
Others	11	8.9%
Total	123	100%
Geographic Distribution		
Europe	45	36,59%
Asia	42	34,15%
North America	15	12,20%
MENA	8	6,50%
Multi-country	13	10,57%
Total	123	100%
Industry Distribution		
Automotive	28	22,76%
Electronics	22	17,89%
Metalworking	18	14,63%
Food	15	12,20%
Machinery	14	11,38%
Multi-industry	26	21,14%
Total	123	100%

3.1.1 Research Methodology and Empirical Context

With respect to research design, the majority of studies employ case study methodologies, often focusing on single organizations. These studies adopt both quantitative approaches (e.g., analysis of firm-level datasets) and qualitative approaches (e.g., interviews with managers and practitioners). A considerable number of contributions also rely on survey-based methods, reflecting an increasing interest in capturing perceptions, adoption drivers, and organizational readiness related to AI. Only a limited subset of studies adopts mixed-method approaches, combining qualitative and quantitative evidence to provide more comprehensive insights (e.g., Bodendorf et al., 2023).

In terms of empirical context, the literature is predominantly concentrated in European and Asian regions, with comparatively fewer studies focusing on North America or emerging economies. Some contributions adopt a broader geographical perspective, analyzing multiple countries or regions (e.g., Kinkel et al., 2023; Al-Surmi et al., 2022).

From an industry perspective, the automotive sector emerges as the most extensively investigated context, likely due to its high level of technological maturity and data availability. This is followed by industries such as electronics, metalworking, food processing, and machinery manufacturing. A number of studies adopt a cross-industry perspective or examine manufacturing firms more generally (e.g., Meyer & Henke, 2023; Usuga-Cadavid et al., 2022; Leoni et al., 2022), thereby enhancing the generalizability of findings.

This distribution of methodologies and empirical contexts reflects broader trends in AI research, where exploratory and context-specific approaches remain dominant due to the evolving nature of the technology. Recent studies suggest a gradual shift toward more large-scale, multi-method, and longitudinal designs to improve generalizability and causal inference (McKinsey & Company, 2025; Deloitte, 2026). At the same time, the concentration of studies in technologically advanced regions and industries highlights potential biases in the current literature and underscores the need for more research in underrepresented contexts, including developing economies and service-oriented supply chains (World Economic Forum, 2025; Accenture, 2025).

Future research is therefore encouraged to diversify empirical settings, adopt more robust methodological designs, and explore cross-country comparisons to better capture the global and heterogeneous nature of AI adoption in supply chain management.

3.1.2 SCOR Process Coverage

The analysis of SCOR processes reveals an uneven distribution of research focus across supply chain activities. A substantial proportion of studies concentrates on the “Make” and “Enable” processes, emphasizing the role of AI in optimizing production-related activities. These include applications such as predictive maintenance, quality control, cost reduction, process optimization, and resource efficiency, as well as broader performance improvements in terms of flexibility, agility, and innovation.

Significant attention is also directed toward the “Plan” and “Source” processes. Within these domains, AI is commonly applied to demand forecasting, inventory optimization, supplier selection, and procurement analytics, reflecting the importance of data-driven decision-making in upstream supply chain activities.

In contrast, the “Deliver” and “Return” processes remain relatively underexplored. Existing studies in these areas are limited and primarily focus on logistics optimization and warranty or return prediction, suggesting potential gaps in the literature.

Notably, several studies adopt a holistic perspective, examining multiple SCOR processes simultaneously (e.g., Source–Make–Deliver or end-to-end supply chain integration). These contributions often address broader themes such as supply chain resilience, coordination, and system-wide optimization (e.g., Manimuthu et al., 2022a; Cannas et al., 2023).

This uneven distribution reflects broader technological and organizational priorities, where AI adoption is often driven by areas with high data availability and immediate efficiency gains, such as production and planning. Recent studies indicate a growing shift toward expanding AI applications into downstream activities, particularly logistics, last-mile delivery, and reverse logistics, driven by the rise of e-commerce and sustainability concerns (McKinsey & Company, 2025; World Economic Forum, 2025).

Moreover, emerging research highlights the increasing importance of integrating AI across end-to-end supply chain processes to enable real-time visibility, autonomous decision-making, and coordinated optimization across multiple nodes (Deloitte, 2026; Accenture, 2025). This suggests that future research should move beyond isolated process-level applications and adopt more systemic and network-oriented perspectives, particularly in underexplored domains such as “Deliver” and “Return.”

3.1.3 AI Approaches, Techniques, and Data Characteristics

In terms of technological approaches, the majority of studies focus on Machine Learning (ML) applications. Among these, supervised learning techniques are the most prevalent, reflecting their suitability for prediction and classification tasks in structured industrial environments. Specifically, 42 studies employ supervised learning, while fewer studies utilize unsupervised learning (5), semi-supervised learning (1), or hybrid approaches combining multiple learning paradigms (10).

Regarding analytical purposes, AI applications are primarily oriented toward regression (26 studies) and classification (15 studies), with some studies combining both approaches (6). Other applications, such as clustering and anomaly detection, are comparatively less represented, indicating opportunities for further exploration.

At the level of specific techniques, the most frequently adopted models include: (1) Random Forest (2) Artificial Neural Networks (ANN) (3) Linear Regression (4) Support Vector Machines (SVM) (5) Extreme Gradient Boosting (XGBoost) (6) K-Nearest Neighbors (KNN) (7) Support Vector Regression (SVR)

This distribution reflects a preference for well-established, interpretable, and scalable algorithms suitable for industrial applications.

Finally, the analysis of data inputs highlights the diversity of data sources used in AI-driven SCM research. The most common categories include: (1) Production and operational data (e.g., process parameters, production schedules) (2) Product-related data (e.g., costs, specifications) (3) Demand data (e.g., orders, pricing, promotions) (4) Sourcing and procurement data (e.g., lead times, transaction volumes) (5) Machine and maintenance data (e.g., failure rates, maintenance frequency) (6) After-sales data (e.g., warranty claims) (7) Macroeconomic indicators (e.g., exchange rates) (8) External data sources, including social media signals

In many cases, studies integrate multiple data types, highlighting the increasing importance of data fusion and multi-source analytics in enhancing predictive accuracy and decision-making effectiveness within supply chains.

3.2 Thematic Findings

This section presents the results of the inductive coding process and synthesizes the key insights emerging from the reviewed articles. Building on the coding framework , the analysis identifies four overarching and interrelated research themes: (1) data and system requirements, (2) technology deployment processes, (3) inter- and intra-organizational integration, and (4) performance implications. In addition, several contextual factors are found to influence all themes.

These themes reflect the dominant areas of inquiry within empirical research on Artificial Intelligence (AI) in Supply Chain Management (SCM), while also highlighting important gaps and emerging research opportunities.

3.2.1 Data and System Requirements

A fundamental theme across the literature concerns the data and technological infrastructure required to successfully implement AI in supply chains. The findings consistently emphasize that data availability, quality, and integration represent critical prerequisites for AI adoption.

Empirical studies highlight that AI systems rely heavily on large volumes of structured and high-quality data, often sourced from multiple internal and external systems such as ERP, IoT devices, and supplier databases. However, many organizations face significant challenges related to data silos, inconsistency, and lack of standardization, which hinder effective AI deployment.

Furthermore, the literature underscores the importance of IT infrastructure readiness, including cloud computing capabilities, data storage systems, and real-time processing architectures. Several studies also point to the role of data governance mechanisms, emphasizing issues such as data ownership, privacy, and security.

Overall, the evidence suggests that without a solid data foundation and integrated system architecture, the potential benefits of AI in SCM cannot be fully realized.

3.2.2 Technology Deployment Processes

The second theme focuses on the processes through which AI technologies are implemented and operationalized within supply chains. The findings reveal that AI adoption is not a one-time event but rather a multi-stage, iterative process involving experimentation, piloting, scaling, and continuous improvement.

Most organizations are currently positioned in the early stages of AI maturity, engaging in pilot projects rather than full-scale deployment. Key challenges identified include:(1) Lack of technical expertise and skilled personnel (2) High implementation costs and uncertain return on investment (3) Integration difficulties with legacy systems (4) Resistance to change among employees

The literature also emphasizes the importance of organizational learning and capability development, particularly in building internal competencies related to data analytics and AI management. In addition, top management support and strategic alignment are identified as critical enablers of successful AI implementation.

Overall, the findings indicate that AI deployment in SCM is a complex socio-technical process, requiring alignment between technological capabilities, organizational structures, and human resources.

3.2.3 Inter- and Intra-Organizational Integration

A third key theme concerns the role of AI in facilitating integration within and across organizational boundaries. Supply chains are inherently networked systems, and the effectiveness of AI applications depends on the degree of coordination among different actors.

At the intra-organizational level, AI is used to enhance integration across functional areas such as procurement, production, and logistics. This leads to improved information sharing, decision-making synchronization, and process optimization.

At the inter-organizational level, AI supports collaboration between supply chain partners by enabling: (1) Real-time data sharing (2) Improved demand visibility (3) Enhanced supplier coordination (4) Risk monitoring and mitigation

However, the literature also identifies several barriers to integration, including lack of trust, data sharing reluctance, and misaligned incentives among partners. These challenges highlight the importance of governance mechanisms and relational capabilities in AI-enabled supply chains.

3.2.4 Performance Implications

The fourth theme addresses the impact of AI adoption on supply chain performance. Empirical evidence suggests that AI can generate significant benefits across multiple dimensions, including: (1) Operational efficiency (e.g., cost reduction, process optimization) (2) Responsiveness and agility (e.g., faster decision-making, demand adaptation) (3) Innovation capability (e.g., new business models and processes) (4) Resilience (e.g., improved risk prediction and disruption management)

However, the findings also reveal that performance outcomes are not uniform and often depend on contextual factors such as organizational readiness, data quality, and integration capabilities. Some studies report limited or delayed performance gains, particularly when AI implementation is fragmented or poorly aligned with organizational strategy.

This suggests that AI should not be viewed as a standalone solution, but rather as part of a broader capability-building process within supply chains.

3.2.5 Contextual Factors

Across all themes, the analysis identifies several contextual factors that influence the adoption and effectiveness of AI in SCM. These include: (1) Industry characteristics (e.g., level of digitalization, complexity) (2) Firm size and resources (3) Regulatory environment (4) Technological maturity (5) Cultural and organizational factors

These elements shape both the opportunities and constraints associated with AI implementation, reinforcing the need for context-sensitive research and managerial approaches.

3.2.6. Synthesis of Thematic Insights

Taken together, the four themes highlight that the implementation of AI in SCM is not purely a technological endeavor but rather a multi-dimensional transformation process. Successful adoption requires the alignment of data infrastructure, organizational capabilities, inter-firm relationships, and strategic objectives.

While the literature demonstrates significant potential for AI to transform supply chains, it also reveals important gaps—particularly in relation to underexplored SCOR processes (e.g., Deliver and Return), cross-organizational dynamics, and long-term performance implications.

3.3. Data and System Requirements

The first theme—data and system requirements—emerges as the most extensively addressed dimension in the reviewed literature, being covered by 94 studies (76%). This theme encompasses the characteristics of data inputs and the technological infrastructure necessary to enable effective AI implementation in supply chain contexts. It is structured into three interrelated categories: (3.3.1) accessing data, (3.3.2) developing the technological backbone, and (3.3.3) adopting complementary technologies.

3.3.1. Accessing Data (79 articles, 64%)

A substantial body of research emphasizes that the effectiveness of AI systems is fundamentally dependent on data availability, quality, and volume, consistent with the well-established "garbage in–garbage out" principle (Brock & von Wangenheim, 2019; Demlehner et al., 2021). This is particularly critical for machine learning (ML) applications, which require large-scale, high-dimensional datasets to ensure robust model training and reliable predictive performance (Brintrup et al., 2020; El Garrab et al., 2023). Empirical evidence suggests that larger datasets generally enhance analytical accuracy (Ji et al., 2021), especially in contexts involving real-time decision-making and autonomous process execution, where both historical and streaming data are required (Budak & Sarvari, 2021; Cadden et al., 2022; Hu et al., 2023).

However, data volume alone is insufficient when data quality is compromised. Studies consistently highlight challenges related to missing, incomplete, or inconsistent data, which can significantly reduce model reliability (Loyer et al., 2016; Perno et al., 2023; Sen et al., 2023). While AI techniques can partially mitigate such issues through adaptive learning and imputation methods (Msakni et al., 2023; Senoner et al., 2022; Takeda-Berger & Frazzon, 2024), this often requires careful model selection and simplification, particularly in contexts characterized by limited or low-quality datasets (Sohrabpour et al., 2021; Vanderschueren et al., 2023). In such cases, human intervention remains essential to support data preprocessing and model validation (Burger et al., 2023; Oberdorf et al., 2021).

Organizational capabilities in data management play a critical role in facilitating AI adoption. Firms with established data governance practices are better positioned to leverage AI technologies (Brock & von Wangenheim, 2019), whereas those lacking confidence in their data quality often exhibit reluctance toward implementation (Meyer & Henke, 2023; Nayal et al., 2022). A significant proportion of project effort—estimated at 50–80%—is devoted to data collection, cleaning, and preparation (Bodendorf et al., 2022a). Moreover, in large organizations, data are frequently distributed across multiple functional units, necessitating the development of integrated data pipelines and architectures (Hasija & Esper, 2022).

Data-related challenges are further amplified in inter-organizational contexts, where issues of data availability, trustworthiness, and standardization become critical (Bodendorf et al., 2022a; Cannas et al., 2023). Data quality must also be continuously reassessed over time, as training datasets may become obsolete due to system changes, stochastic variability, or data corruption (Bokrantz et al., 2023; Manimuthu et al., 2022b).

In addition, concerns related to data security and confidentiality are frequently highlighted as key barriers to AI adoption. Effective governance mechanisms—including formal policies, clearly defined responsibilities, and cybersecurity measures—are essential to ensure data protection and compliance (Chatterjee et al., 2023; Leberruyer et al., 2023; Sodhi et al., 2022; Yadav et al., 2020).

Closely related is the issue of data sharing across supply chain partners, which remains a persistent challenge in SCM (Kembro & Näslund, 2014). Barriers such as lack of trust, high investment costs, and misaligned incentives continue to limit data exchange (Bodendorf et al., 2022b; Cannas et al., 2023). Nevertheless, the literature suggests that these barriers can be mitigated through long-term collaboration, benefit-sharing mechanisms, and advanced data-sharing models, including the use of third-party digital platforms (Cadden et al., 2022; Chatterjee et al., 2023; Guida et al., 2023b).

Finally, emerging research highlights the role of alternative data sources and methods to reduce data dependency. AI systems can process unstructured data (e.g., web data, news feeds, social media), enabling new forms of inference without relying solely on internal organizational data (Brintrup et al., 2023; Chatterjee et al., 2023; Pessot et al., 2022). Additional approaches include the use of synthetic or semi-synthetic data for model training (Vanderschueren et al., 2023) and federated learning, which enables collaborative model development without direct data sharing (Manimuthu et al., 2022a; Zheng et al., 2023).

3.3.2. Developing the Technological Backbone (25 articles, 20%)

The second category emphasizes the importance of establishing a robust technological infrastructure to support AI applications. Despite declining costs of computing power, AI implementation still requires substantial hardware, software, and connectivity resources (Bokrantz et al., 2023). Many firms face limitations in terms of IT infrastructure readiness, including insufficient broadband capacity and lack of advanced data processing systems (Bodendorf et al., 2022a; Cannas et al., 2023).

Two key components of the technological backbone are identified:

(1) data collection and storage systems, and (2) computational capabilities for data processing and model execution (Helo & Hao, 2022; Xia et al., 2022).

At the operational level, firms often need to integrate multiple systems, such as Manufacturing Execution Systems (MES), Supervisory Control and Data Acquisition (SCADA), and Programmable Logic Controllers (PLC), to enable seamless data flows (Oberdorf et al., 2021). However, integration challenges frequently arise due to the presence of legacy systems, particularly in complex supply chain environments involving multiple stakeholders (Brock & von Wangenheim, 2019; Zhu et al., 2021; Cadden et al., 2022).

To address these challenges, the literature highlights the importance of interoperability, standardization, and semantic data exchange, achieved through common data schemas and shared data dictionaries (Ji et al., 2021; Kosasih et al., 2022; Pillai et al., 2022).

In parallel, the increasing reliance on data-driven systems underscores the critical role of cybersecurity infrastructure, including solutions such as intrusion detection systems and disaster recovery mechanisms (Allal-Chérif et al., 2021; Brock & von Wangenheim, 2019).

3.3.3. Adopting Complementary Technologies (45 articles, 37%)

The third category highlights that AI adoption in supply chains is often embedded within broader digital transformation and Industry 4.0 initiatives (Agrawal & Narain, 2023; Hopkins, 2021). While AI can be implemented as a standalone technology (Brintrup et al., 2023), it is more commonly deployed in combination with complementary technologies that enhance data collection, processing, and automation capabilities.

Among these, the Internet of Things (IoT) and machine connectivity are the most frequently cited, particularly in applications related to quality control, predictive maintenance, and real-time logistics management (Chen et al., 2021; Hoffmann et al., 2021; Kaparthi & Bumblauskas, 2020; Sen et al., 2023; Song et al., 2023).

Cloud computing represents another key enabler, offering scalability, flexible computing resources, and improved collaboration across supply chain actors (Bodendorf et al., 2022a; Xia et al., 2022; Perno et al., 2023).

In inter-organizational contexts, blockchain technology is increasingly explored as a mechanism to enhance data transparency, traceability, and trust (Rodríguez-Espíndola et al., 2022; Yadav et al., 2020).

Finally, AI is often integrated with advanced operational technologies such as robotics, automation systems, drones, wearables, augmented/virtual reality, and additive manufacturing, further expanding its application scope in manufacturing and logistics environments (Pillai et al., 2022; Perno et al., 2023; Song et al., 2023).

3.4 Technology Deployment Process

The second theme—technology deployment process—is addressed by 92 studies (75%) and focuses on how AI solutions are effectively integrated into real-world supply chain environments. This includes activities related to strategy formulation, solution design, implementation, and ongoing monitoring. The literature identifies three key categories: (3.4.1) defining the AI strategy and approach, (3.4.2) designing the technological solution, and (3.4.3) accessing competencies and expertise.

3.4.1. Defining the AI Strategy and Approach (33 articles, 27%)

A central issue in AI deployment concerns investment decisions and resource allocation. The perceived high costs of implementation (Pillai et al., 2022), coupled with limited financial and organizational resources, represent significant barriers to adoption (Mohiuddin et al., 2022; Sodhi et al., 2022). These challenges are particularly pronounced in large-scale or factory-wide applications (Demlehner et al., 2021; Gonçalves et al., 2021). Notably, empirical evidence suggests that the majority of investments are not directed toward AI algorithms per se, but rather toward supporting infrastructure and complementary technologies (Gupta et al., 2022; Hopkins, 2021).

The formulation of an effective AI strategy requires strong leadership involvement. Top management plays a crucial role in articulating a clear vision, allocating resources, and fostering an organizational climate conducive to innovation (Hasija & Esper, 2022; Merhi & Harfouche, 2023). Conversely, insufficient managerial support is associated with lower levels of adoption and limited assimilation (Meyer & Henke, 2023; Mohiuddin et al., 2022).

Strategic alignment between AI initiatives and broader business objectives is also critical. The literature emphasizes the need for coherent digital strategies, rather than fragmented or ad hoc implementations (Brock & von Wangenheim, 2019; Merhi & Harfouche, 2023). Firms often pursue AI adoption to achieve competitive differentiation and to respond to environmental uncertainty (Demlehner et al., 2021; Pillai et al., 2022; Zhu et al., 2021). In some cases, AI adoption leads to fundamental strategic transformations, enabling new business models and operating paradigms (Chen et al., 2022).

An important challenge at this stage is the cost–benefit assessment of AI initiatives. Many firms rely on perceptual or qualitative evaluations, with relatively few developing formal business cases (Dora et al., 2022; Merhi & Harfouche, 2023; Mohiuddin et al., 2022). When applied, evaluation metrics include operational costs, return on investment (ROI), net present value, payback periods, and benchmarking indicators (Meyer & Henke, 2023; Sodhi et al., 2022). However, estimating both costs and expected returns remains difficult due to the lack of historical benchmarks and uncertainty surrounding outcomes (Bodendorf et al., 2022a; Cannas et al., 2023).

To mitigate these uncertainties, several studies advocate for an incremental and iterative deployment approach, allowing organizations to test solutions, learn from pilot projects, and gradually scale implementation (Brock & von Wangenheim, 2019; Meyer & Henke, 2023).

3.4.2. Designing the Technological Solution (65 articles, 53%)

The second category focuses on the design and development of AI models and systems, with particular attention to analytical performance and practical applicability. A key concern in the literature is the accuracy of AI models, with many studies comparing alternative algorithms to identify the most suitable approach for specific use cases (e.g., Abualsauod, 2023). Others evaluate performance improvements by comparing organizational outcomes before and after AI implementation or across multiple cases (e.g., Perno et al., 2023; Sen et al., 2023).

Designing AI solutions involves managing several trade-offs. For instance, higher predictive accuracy often requires greater computational resources, leading to a balance between performance and efficiency (Gonçalves et al., 2021; Hasija & Esper, 2022). Additional trade-offs relate to data characteristics, such as balancing sample size and data quality (Nikolopoulos et al., 2016), as well as error tolerance, considering the operational implications of false positives and false negatives (Flath & Stein, 2018). These considerations should be addressed early in the design phase, as they influence both algorithm selection and performance evaluation metrics (Bokrantz et al., 2023; Chuang et al., 2021).

Another critical aspect concerns model maintenance and updating. Given the dynamic nature of supply chain environments, AI models require continuous monitoring, retraining, and adaptation to reflect changing conditions (Helo & Hao, 2022; Brock & von Wangenheim, 2019). While some studies suggest integrating maintenance activities into ongoing operations (Burger et al., 2023; Gauder et al., 2023), others advocate for a dedicated maintenance phase within the AI lifecycle to ensure systematic monitoring and updating (Bokrantz et al., 2023).

Maintenance activities include tracking input data quality, detecting changes in system behavior, and retraining models with updated datasets. These processes often require the involvement of domain experts and data scientists (Flath & Stein, 2018; Hasija & Esper, 2022). In some advanced cases, automated updating mechanisms—enabled by cloud-based platforms—allow for continuous model retraining and adaptation with minimal human intervention (Perno et al., 2023).

3.4.3. Accessing Competencies and Expertise (45 articles, 37%)

The third category highlights the importance of human capital and organizational capabilities in AI deployment. A recurring theme is the scarcity of technical expertise, particularly in data science, machine learning, and data engineering (Bodendorf et al., 2022a; Budak & Sarvari, 2021). These competencies are essential not only for model development but also for managing data pipelines and ensuring system integration across different stages of implementation (Manimuthu et al., 2022b; Mohiuddin et al., 2022).

Beyond specialized technical roles, the literature emphasizes the need for cross-functional integration of expertise, where data scientists collaborate closely with supply chain professionals. At the same time, organizations must invest in developing basic digital literacy across the workforce, enabling employees to effectively interact with AI systems (Burger et al., 2023; Hasija & Esper, 2022).

Additional competencies are required in areas such as cybersecurity, user experience design, and hardware technologies (e.g., sensors and actuators), reflecting the multidisciplinary nature of AI-enabled systems (Kinkel et al., 2022; 2023). The lack of skilled personnel is consistently identified as a major barrier to AI adoption, particularly for firms with limited resources to attract and retain talent (Demlehner et al., 2021; Guida et al., 2023b; Babina et al., 2024; Dey et al., 2023).

Equally important is the role of domain-specific knowledge, which is essential for tasks such as feature selection, model interpretation, and contextualization of analytical outputs (Brintrup et al., 2020; El Garrab et al., 2023; Kang & Kang, 2021). Effective AI solutions require a deep understanding of supply chain processes to ensure that models accurately reflect real-world dynamics.

To address capability gaps, firms increasingly engage in collaborations with external partners, including technology providers, consulting firms, and academic institutions. These partnerships enable access to specialized knowledge, advanced tools, and shared data resources, thereby facilitating AI adoption and innovation (Cannas et al., 2023; Meyer & Henke, 2023).

3.5. (Inter)Organizational Integration

The third theme—(inter)organizational integration—is addressed by 91 studies (74%) and focuses on how AI technologies interact with organizational structures, processes, and human actors within and across supply chains. This theme highlights the socio-technical nature of AI implementation, emphasizing the alignment between technological systems and organizational contexts. Four key categories emerge: (3.5.1) managing acceptance and sensemaking, (3.5.2) redefining job content, (3.5.3) structure and process design, and (3.5.4) adapting supply chain structures and relationships.

3.5.1. Managing Acceptance and Sensemaking (35 articles, 28%)

A central issue in AI integration concerns organizational acceptance and sensemaking, particularly as firms are still experimenting with and adapting to AI technologies (Sodhi et al., 2022). Organizational culture plays a pivotal role in shaping attitudes toward AI, acting as a foundation of shared values, beliefs, and practices (Chatterjee et al., 2021; Merhi & Harfouche, 2023).

The literature emphasizes the importance of fostering a "failure-tolerant culture", which encourages experimentation and risk-taking (Brock & von Wangenheim, 2019; Meyer & Henke, 2023), as well as a data-driven culture where employees are accustomed to using and interpreting data in decision-making processes (Dey et al., 2023; Oberdorf et al., 2021). Effective change management initiatives, including incentive systems and transparent communication, are critical to support technology adoption (Dora et al., 2022; Leberruyer et al., 2023). These cultural dimensions are equally relevant in inter-organizational contexts, where trust and long-term relationships facilitate AI integration across supply chain partners (Cadden et al., 2022; Pessot et al., 2022).

Another key challenge relates to trust in AI systems, particularly due to the "black-box" nature of many advanced models. While black-box models often deliver superior predictive performance, their lack of transparency can hinder user acceptance (Flath & Stein, 2018). In contrast, more interpretable ("white-box") models may enhance trust but at the cost of reduced accuracy.

To address this trade-off, several mitigation strategies are proposed, including: (1) integrating explainable AI mechanisms (Kosasih et al., 2022), (2) clearly defining accountability structures for AI-driven decisions (Hasija & Esper, 2022), (3) providing employee education and training on AI systems (Meyer & Henke, 2023), and (4) involving end-users in development and evaluation processes (Oberdorf et al., 2021).

Over time, trust may also develop organically through repeated interaction and positive experiences with AI systems (Bodendorf et al., 2022a).

The literature also highlights workforce-related concerns, particularly fears of job displacement and reduced job meaningfulness due to automation (Cadden et al., 2022; Mohiuddin et al., 2022). These concerns are especially pronounced among operational and blue-collar workers (Hasija & Esper, 2022) and may negatively affect job engagement and organizational performance (Braganza et al., 2022; Chatterjee et al., 2022b). In this context, managerial awareness and communication are essential to guide organizational change and reinforce the perceived value of AI (Guida et al., 2023b; Rodríguez-Espíndola et al., 2022).

3.5.2. Redefining Job Content (26 articles, 21%)

AI adoption significantly reshapes job roles, task structures, and skill requirements. A key aspect is task automation, particularly in data-intensive activities such as analytics, forecasting, and operational decision-making (Brock & von Wangenheim, 2019; Xia et al., 2022). For example, AI applications in procurement enable automation of supplier selection, contract analysis, and negotiation support, while also facilitating interactions through cognitive assistants (Cannas et al., 2023; Meyer & Henke, 2023).

Automation extends to planning and forecasting processes (Nikolopoulos et al., 2016) and even to supply chain configuration decisions, allowing firms to respond dynamically to disruptions (Hopkins, 2021; Modgil et al., 2022). However, for tasks characterized by high uncertainty and variability, human-in-the-loop systems remain essential, combining algorithmic capabilities with human judgment (Mohiuddin et al., 2022; Oberdorf et al., 2021).

While automation improves efficiency, it also raises concerns regarding dehumanization and over-reliance on technology (Allal-Chérif et al., 2021). Consequently, AI adoption leads to a redefinition of job roles, shifting employees' focus from routine tasks to more strategic, analytical, and relational activities (Bodendorf et al., 2022a; Nikolopoulos et al., 2016).

Rather than replacing human labor, AI increasingly augments human capabilities, enabling enhanced decision-making, multilingual communication, and advanced risk detection (Allal-Chérif et al., 2021; Modgil et al., 2022). This evolution gives rise to hybrid human–AI work systems, where complementary strengths are leveraged (Burger et al., 2023).

As a result, organizations must invest in workforce upskilling and continuous training. Beyond initial tool-specific training, employees require ongoing development of digital and analytical competencies (Dey et al., 2023; Hasija & Esper, 2022). Structured training programs can improve both acceptance and effective utilization of AI systems (Bag et al., 2021; Dora et al., 2022). However, significant challenges remain due to skills shortages and high training costs, particularly in operational environments (Mohiuddin et al., 2022; Sodhi et al., 2022).

3.5.3. Structure and Process Design (67 articles, 54%)

AI adoption has profound implications for organizational processes and structural design. A recurring finding is the strong link between AI and process digitalization and standardization. On one hand, prior digitalization and standardized processes are often preconditions for effective AI implementation (Bodendorf et al., 2022a). Firms that have already adopted digital interfaces, integrated management systems, and lean practices are better positioned to deploy AI solutions (Leoni et al., 2022; Yadav et al., 2020).

On the other hand, AI adoption itself acts as a driver of further digitalization and process redesign, enabling firms to standardize operations, streamline communication, and improve efficiency (Bokrantz et al., 2023; Allal-Chérif et al., 2021; Guida et al., 2023b). Many organizations adopt a phased approach, starting with specific processes—often planning—and progressively extending digitalization across the supply chain (Loyer et al., 2016; Mohan et al., 2023; Takeda-Berger & Frazzon, 2024).

A key dimension of integration concerns the role of AI in decision-making processes. AI systems enhance managerial decision-making by enabling faster data processing, advanced analytics, and real-time insights (Abualsauod, 2023; Paul et al., 2015). They also provide access to new data sources, facilitate scenario analysis, and support prioritization and adaptive decision models (Al-Surmi et al., 2022; Modgil et al., 2022; Islam et al., 2021; Usuga-Cadavid et al., 2022; Kim, 2023).

Despite these advancements, human oversight remains essential, with managers responsible for interpreting outputs, ensuring alignment with organizational goals, and combining AI insights with experiential knowledge (Bodendorf et al., 2022a; Burger et al., 2023; Leberruyer et al., 2023).

From an organizational design perspective, AI is often associated with greater decentralization and flatter structures, which enable faster decision-making (Xia et al., 2022). However, excessive decentralization may lead to data silos and coordination challenges, potentially reducing AI effectiveness (Guida et al., 2023b).

To address this, firms frequently implement cross-functional coordination mechanisms and establish dedicated digital or AI units to support integration efforts (Bodendorf et al., 2022a; Bokrantz et al., 2023; Leberruyer et al., 2023; Sodhi et al., 2022).

3.5.4. Adapting Supply Chain Structures and Relationships (24 articles, 20%)

The final category highlights the implications of AI for supply chain structures and inter-organizational relationships. Effective AI deployment often requires data sharing, coordination, and alignment across supply chain partners (Dora et al., 2022; Pessot et al., 2022).

Key success factors include: (1) early agreement on shared objectives and value distribution, (2) continuous communication and feedback mechanisms, and (3) strong relational foundations based on trust and collaboration (Olan et al., 2022; Zhu et al., 2021; Meyer & Henke, 2023).

AI also contributes to a reconfiguration of supply chain networks. For instance, it enables firms to identify new suppliers beyond traditional networks (Allal-Chérif et al., 2021), optimize sourcing strategies, and assess supply chain risks more effectively (Wong et al., 2022).

Furthermore, AI-driven automation and analytics may influence production location decisions, including reshoring strategies, due to reduced labor dependency and increased emphasis on technological capabilities (Kinkel et al., 2023).

Overall, AI not only enhances operational efficiency but also reshapes the structural and relational dynamics of supply chains, driving new forms of collaboration and network design.

3.6 Performance Implications

The fourth theme—performance implications—is addressed by 89 studies (72%) and examines the outcomes associated with AI adoption in Supply Chain Management (SCM). The literature predominantly reports evidence from single-case applications (e.g., Kang & Kang, 2021; Senoner et al., 2022) and multiple case studies (e.g., Burger et al., 2023; Helo & Hao, 2022), with many findings based on perceived or expected benefits rather than fully validated longitudinal evidence. Empirical validation remains relatively limited, as survey-based studies often rely on expert opinions rather than direct organizational experience (e.g., Cadden et al., 2022; Sodhi et al., 2022), although some contributions leverage secondary datasets (e.g., Babina et al., 2024).

Two major dimensions of performance emerge from the analysis: (3.6.1) improvements in operational performance and (3.6.2) enhancement of organizational capabilities.

3.6.1. Improving Operational Performance (66 articles, 54%)

A substantial body of literature highlights AI's contribution to operational efficiency and effectiveness, ranging from aggregate performance improvements (e.g., Chatterjee et al., 2022; Leoni et al., 2022) to specific operational metrics such as cost, time, quality, and flexibility.

One of the most frequently reported benefits is cost reduction, driven by process optimization and enhanced decision-making. In production environments, AI enables predictive maintenance and real-time process adjustments, maximizing machine utilization and reducing downtime (Mjimer et al., 2023; Msakni et al., 2023). Additionally, AI models can incorporate targeted cost functions, improving cost control and resource allocation (Manimuthu et al., 2022a; 2022b). Reductions in defective products further generate savings in logistics, rework, and disposal (Leberruyer et al., 2023).

In planning processes, AI enhances forecasting accuracy, enabling better inventory management, reduced stock levels, and improved stock rotation. These improvements positively affect working capital efficiency and financial performance indicators, such as return on assets (Chuang et al., 2021; Gonçalves et al., 2021; Feizabadi, 2022). At a strategic level, AI-supported analytics facilitate more informed managerial decisions, contributing to overall profitability (Budak & Sarvari, 2021; Senoner et al., 2022).

AI also drives time efficiency improvements by streamlining processes such as supplier selection, procurement analysis, bidding, and order management (Bodendorf et al., 2022c; Budak & Sarvari, 2021). Moreover, AI enables near real-time coordination across supply chain actors, particularly in logistics operations (Sodhi et al., 2022; Wong et al., 2022; Chen et al., 2021). These advancements lead to reduced lead times and improved delivery performance, including higher on-time delivery rates (Bodendorf et al., 2022a; Burger et al., 2023).

Automation capabilities further enhance time performance by enabling dynamic adjustment of machine parameters, optimized routing decisions, and efficient coordination of robots and assembly systems (Hu et al., 2023; Xia et al., 2022; Cannas et al., 2023).

Another critical dimension is quality improvement and process reliability. AI applications support defect detection, root-cause analysis, and predictive quality control (Crespo et al., 2020; Kang & Kang, 2021; Msakni et al., 2023). Compared to traditional methods, AI-based inspection systems offer higher accuracy and adaptability, enabling a shift from sample-based to full-scale quality inspection (Helo & Hao, 2022; Dengler et al., 2021; Song et al., 2023). These improvements extend beyond production to areas such as document processing and procurement, where predictive analytics enhances decision accuracy and supplier reliability (Burger et al., 2023; Allal-Chérif et al., 2021).

Finally, AI contributes to enhanced operational flexibility, defined as the ability to respond rapidly to changes in demand and supply conditions. The integration of AI with automation technologies (e.g., robotics and drones) allows firms to dynamically adapt production and logistics operations (Demlehner et al., 2021; Enrique et al., 2022). AI also supports supplier switching and capacity prediction, enabling more agile sourcing decisions (Brintrup et al., 2020; Burger et al., 2023). Additionally, predictive capabilities allow organizations to anticipate regulatory changes and market fluctuations, further strengthening adaptability (Gupta et al., 2023; Wong et al., 2022).

3.6.2. Enhancing Organizational Capabilities (58 articles, 47%)

Beyond operational improvements, AI adoption contributes to the development of higher-order organizational capabilities, particularly in the areas of risk management, innovation, customer relationship management, and sustainability.

A major capability enhanced by AI is supply chain resilience and risk management. AI systems enable the early detection of anomalies, prediction of potential disruptions, and proactive mitigation of risks (Kaparthi & Bumblauskas, 2020; Leukel et al., 2023). In planning contexts, AI reduces risks associated with demand volatility through improved forecasting accuracy (Gonçalves et al., 2021; Manimuthu et al., 2022a; 2022b).

In logistics, AI supports real-time monitoring and adaptive decision-making, such as dynamic vehicle rerouting in response to disruptions (Chen et al., 2021; Gupta et al., 2022). In supplier management, AI can process both internal and external data sources to automate risk assessment and enforce compliance policies (Allal-Chérif et al., 2021; Brintrup et al., 2020). These capabilities reduce information blind spots and enable faster, more effective responses to disruptions (Burger et al., 2023; Nayal et al., 2022).

At the network level, AI facilitates multi-tier supply chain visibility, uncovering hidden interdependencies and supporting advanced scenario analysis, including stress testing and "what-if" simulations (Kosasih et al., 2022; Modgil et al., 2022). It also contributes to financial resilience by improving decision-making under uncertainty (Gupta et al., 2023; Olan et al., 2022).

Another important capability relates to innovation and customer relationship management. AI enhances customer-centric strategies by enabling advanced segmentation, targeting, and personalization, leading to improved customer satisfaction and increased sales (Cadden et al., 2022; Hopkins, 2021; Helo & Hao, 2022). AI-driven analytics also support new product development and market intelligence, facilitating innovation processes (Babina et al., 2024; Mohiuddin et al., 2022; Pessot et al., 2022).

In addition, AI enables dynamic pricing strategies and improves the efficiency of sales and quoting processes through automated configurators and decision-support tools (Budak & Sarvari, 2021; Helo & Hao, 2022). Customer interfaces are further enhanced through the use of chatbots and intelligent assistants, improving responsiveness and service quality (Wong et al., 2022).

Finally, AI contributes to sustainability capabilities, both environmental and social. From an environmental perspective, AI supports waste reduction, energy optimization, and improved recycling processes, contributing to lower emissions and more efficient resource use (Cannas et al., 2023; Demlehner et al., 2021; Manimuthu et al., 2022a). AI-enabled supplier selection tools can also incorporate environmental criteria, promoting greener supply chains (Kuo et al., 2010).

From a social sustainability standpoint, AI-driven automation of hazardous tasks and the use of collaborative robots (cobots) enhance worker safety and well-being (Cannas et al., 2023). More broadly, AI-enabled data analytics support the transition toward circular economy practices and sustainable manufacturing systems (Dey et al., 2023; Yadav et al., 2020).

3.7 Contextual Factors

The final theme—contextual factors—is addressed by 40 studies (33%) and reflects the context-dependent nature of empirical research on Artificial Intelligence (AI) in Supply Chain Management (SCM). Given the predominance of single-case and case-based studies, the findings in the literature are often shaped by specific organizational, industrial, and institutional settings. Nevertheless, several cross-cutting contextual dimensions emerge that influence all previously identified themes.

First, the competitive environment plays a critical role in shaping AI adoption and implementation. Industry-specific competitive pressures often act as key drivers, pushing firms to explore and deploy AI technologies to maintain or enhance their market position. The selection of AI tools and implementation approaches is typically aligned with strategic priorities, such as cost leadership, quality differentiation, or service excellence (Chatterjee et al., 2021; Dora et al., 2022; Al-Surmi et al., 2022; Kinkel et al., 2022). This suggests that AI adoption is not uniform but rather contingent upon firms' competitive strategies and industry dynamics.

Second, several studies highlight the role of external shocks, particularly the COVID-19 pandemic, in accelerating AI adoption. Organizations leveraging AI capabilities demonstrated greater effectiveness in managing operational disruptions, supply chain finance, and demand uncertainty during the crisis (Gupta et al., 2022; Olan et al., 2022). Moreover, AI applications were specifically developed or repurposed to address pandemic-related challenges, such as demand forecasting under extreme uncertainty and disruption management (Raghuram et al., 2023; Zheng et al., 2023). These findings underline the role of AI as a crisis-response and resilience-enabling technology.

Third, institutional factors, policies, and regulatory frameworks significantly influence AI implementation. Institutional environments shape organizational attitudes toward innovation and experimentation, particularly through cultural norms that either facilitate or hinder the adoption of emerging technologies (Dey et al., 2023). In addition, the presence of supportive policies, financial incentives, and clear regulatory guidelines—especially regarding data governance, privacy, and data residency—encourages firms to invest in AI solutions (Bag et al., 2021; Dora et al., 2022). Conversely, regulatory uncertainty may slow down adoption due to perceived risks.

Finally, firm size emerges as an important contingency factor. Larger organizations typically possess greater technological readiness, financial resources, and access to skilled talent, enabling more extensive and sophisticated AI implementations (Babina et al., 2024). In contrast, small and medium-sized enterprises (SMEs) may face constraints related to resource availability, expertise, and infrastructure, which can limit both adoption and performance outcomes. This highlights the uneven distribution of AI capabilities across firms and underscores the importance of resource-based differences in shaping AI adoption trajectories.

4. Discussion and Research Agenda

The primary objective of this study was to examine empirical research on Artificial Intelligence (AI) in Supply Chain Management (SCM) in order to provide a comprehensive understanding of the current state of knowledge and the emerging discontinuities introduced by this technology (RQ1). Building on the findings of the systematic literature review (SLR), this section first synthesizes the key insights and then outlines a research agenda to guide future scholarly inquiry (RQ2).

4.1 Discussion of Key Findings (RQ1)

The main insights derived from the SLR which contrasts elements that are specific to AI and potentially disruptive with those that are more broadly aligned with existing digital transformation and Industry 4.0 trends. Across the four themes identified earlier, four key insights emerge.

4.1.1. Insight 1: Data as a Critical Enabler—With Emerging Alternatives to Traditional Limitations

A fundamental requirement for AI effectiveness lies in the availability, quality, and volume of data. This finding aligns with prior research on digital technologies in SCM, where data access—particularly in inter-organizational contexts—has long been recognized as a major challenge (e.g., Culot et al., 2024; Kembro & Näslund, 2014).

However, the SLR highlights an important discontinuity: AI technologies demonstrate an increasing ability to operate under imperfect data conditions. For instance, AI can extract insights from limited or low-quality internal datasets, leverage external and third-party data sources, and utilize federated learning approaches to analyze distributed data without requiring full data sharing (Brintrup et al., 2023; Bodendorf et al., 2022b; Zheng et al., 2023).

These developments suggest a shift from traditional data dependency toward more flexible and adaptive data utilization mechanisms, potentially reducing long-standing barriers to inter-organizational data sharing in supply chains.

4.1.2 Insight 2: AI Deployment as a Continuous and Evolving Process

The deployment of AI differs from traditional information systems in that it is inherently dynamic and iterative. AI implementation involves not only initial development and integration but also continuous monitoring, retraining, and adaptation over time.

Unlike many digital technologies, the value of AI systems tends to increase progressively as they are exposed to larger and more diverse datasets, enabling improved learning and predictive accuracy (Bokrantz et al., 2023; Hasija & Esper, 2022).

Furthermore, the literature points to emerging opportunities for the automation of AI lifecycle activities, including model design, updating, and maintenance through cloud-based and third-party services (Perno et al., 2023). While these developments can enhance scalability and efficiency, they also introduce new risks related to dependence on external providers, data governance, and system transparency.

4.1.3. Insight 3: AI Reshapes (Inter)Organizational Processes and Decision-Making Authority

AI exerts a profound impact on organizational and inter-organizational processes, particularly in relation to automation and decision-making. While automation is not unique to AI (Culot et al., 2020; Frank et al., 2019), AI represents a significant evolution in that it enables the delegation of not only tasks but also decision-making authority to technological agents (Belhadi et al., 2022; Hasija & Esper, 2022).

This shift introduces new complexities, especially when dealing with autonomous and opaque ("black-box") models, where decision logic is not easily interpretable (Guida et al., 2023b). The challenge becomes even more pronounced in inter-organizational contexts, where trust, accountability, and coordination across multiple actors are required.

As a result, AI adoption necessitates new approaches to governance, transparency, and human–machine interaction, redefining traditional roles and responsibilities within supply chains.

4.1.4. Insight 4: AI as a Driver of Enhanced and Novel Organizational Capabilities

The SLR demonstrates that AI contributes to the development of a wide range of organizational capabilities, including operational efficiency, risk management, innovation, and sustainability (Babina et al., 2024).

Importantly, these capabilities are not merely incremental improvements but often represent qualitative shifts in how organizations operate and compete. For example, AI enhances supply chain resilience through predictive analytics and real-time responsiveness, while also enabling new forms of customer engagement and data-driven innovation.

However, the extent to which these capabilities translate into improved performance depends on how and where AI is integrated within organizational processes and supply chain structures. This highlights the importance of contextual and configurational factors in shaping AI outcomes.

4.2 Research Agenda (RQ2)

Building on these insights, this study responds to RQ2 by outlining directions for future research. As emphasized in prior studies on emerging technologies (e.g., Hanelt et al., 2021; Gama & Magistretti, 2023), investigating disruptive phenomena requires reassessing the adequacy of existing theoretical frameworks and identifying areas where new perspectives may be needed.

Future research on AI in SCM should focus on the following key directions:

1) Theorizing Data Ecosystems and Governance
   Future studies should explore how organizations design and manage data ecosystems, particularly in inter-organizational settings. This includes issues related to data sharing, ownership, trust, and governance mechanisms, as well as the role of emerging approaches such as federated learning and synthetic data.
2) Understanding AI Lifecycle and Value Realization
   There is a need for longitudinal research examining the full lifecycle of AI systems, from adoption to scaling and continuous improvement. Scholars should investigate how value is created, captured, and sustained over time, as well as the trade-offs associated with automation and external service provision.
3) Redefining Decision-Making and Governance Structures
   AI-enabled decision-making raises fundamental questions about authority, accountability, and transparency. Future research should examine how organizations redesign governance structures to accommodate human–AI collaboration, particularly in complex supply chain networks.
4) Linking AI to Dynamic Capabilities and Performance
   Further empirical research is needed to understand how AI contributes to the development of dynamic capabilities, such as sensing, seizing, and transforming. This includes identifying the conditions under which AI adoption leads to sustained competitive advantage and improved supply chain performance.
5) Exploring Contextual and Contingency Factors
   Finally, future studies should adopt a contingency perspective, examining how contextual factors—such as industry characteristics, institutional environments, and firm size—influence AI adoption and outcomes. Comparative and cross-country studies would be particularly valuable in this regard.

5. Conclusion

This study presented a systematic literature review (SLR) of 123 empirical articles examining the application of Artificial Intelligence (AI) in Supply Chain Management (SCM). By synthesizing evidence from real-world implementations, the study identified cross-cutting themes and key research topics, which served as the foundation for the development of a comprehensive research agenda. The motivation for this work stemmed from the need to critically assess the gap between the expectations surrounding AI and its actual implementation, thereby enabling more grounded and theoretically robust advancements in the field.

Despite its contributions, this study is subject to several limitations. First, the reviewed body of literature reflects a rapidly evolving research domain, where both technological capabilities and organizational applications are still in flux. While this review extends prior efforts (e.g., Toorajipour et al., 2021; Pournader et al., 2021) by incorporating more recent empirical evidence, the dynamic nature of AI suggests that continuous updates of the literature are necessary to capture ongoing developments.

Second, although the study adopted a rigorous and transparent SLR methodology, the manual selection and coding process may introduce potential bias. However, this limitation is mitigated by the depth of analysis and the use of established methodological guidelines. Additionally, the review exclusively considered peer-reviewed journal articles, thereby excluding other relevant sources such as conference proceedings, books, and gray literature. While this decision ensured academic rigor and quality, it may have limited the inclusion of emerging insights, particularly in a fast-moving field such as AI.

In particular, existing books and practitioner-oriented publications provide valuable perspectives on technical architectures, industry-specific applications, and thematic areas such as sustainability, regulation, and security (e.g., Chatterjee et al., 2022a; Vermesan & Marples, 2024; Kumar et al., 2023). However, many of these contributions either lack empirical validation or focus on conceptual and technical discussions rather than real-world implementation. Future studies may therefore consider integrating such sources through complementary methodologies, such as bibliometric or hybrid reviews, to provide a more holistic understanding.

From a theoretical standpoint, this study offers three main contributions.

First, it provides a systematic and up-to-date overview of empirical research on AI in SCM, consolidating fragmented knowledge and identifying common patterns across application domains. By focusing exclusively on empirically validated studies, the review ensures that insights are grounded in practical evidence rather than speculative claims. Furthermore, the study distinguishes between AI-specific characteristics and broader dynamics associated with digital transformation and Industry 4.0, thereby enhancing conceptual clarity.

Second, the study develops a comprehensive research agenda by linking empirical findings with established and emerging theoretical perspectives in SCM and related disciplines. This approach not only identifies gaps in the current literature but also proposes directions for future inquiry, ranging from data governance and AI lifecycle management to decision-making structures and dynamic capabilities. In doing so, the study contributes to ongoing scholarly efforts to theorize the impact of disruptive technologies (e.g., Hanelt et al., 2021).

Third, the study advances methodological recommendations for future research. In particular, it highlights the need for a more precise operationalization of AI constructs in empirical studies. Researchers are encouraged to strike a balance between technical specificity (e.g., distinguishing among AI techniques) and practical relevance, ensuring that findings remain both rigorous and applicable.

Beyond academic contributions, this study also provides important managerial implications. While AI has become a strategic priority for many supply chain leaders, its implementation remains challenging due to technical, organizational, and inter-organizational barriers (e.g., World Economic Forum, 2023; McKinsey, 2023). The findings of this review emphasize that successful AI adoption extends beyond technology itself, requiring alignment with organizational structures, data capabilities, and supply chain relationships.

Moreover, the study cautions against overly optimistic expectations regarding AI-driven performance improvements. Although the literature highlights numerous potential benefits, robust empirical validation remains limited, suggesting that managers should adopt a measured and evidence-based approach when investing in AI initiatives. Ultimately, AI should be viewed not as a standalone solution, but as part of a broader transformation involving process redesign, capability development, and ecosystem integration.

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Appendix Tables (A1–A6)

Table A1. List of Reviewed Articles (Sample Structure)

No	Author(s)	Year	Journal	Focus Area	Method (Indicative)	Key Contribution
1	Abidi et al.	2014	SCM Int. Journal	Humanitarian SCM	SLR	Performance measurement in supply chains
2	Agrawal & Narain	2023	IJPE	Digital transformation	Empirical	Industry 4.0 improves SC performance
3	Al-Hajj et al.	2020	TR Part E	Predictive logistics	ML model	Hybrid ML improves logistics prediction
4	Allal-Chérif et al.	2021	TFSC	Procurement	Empirical	AI enhances procurement decisions
5	Ardito et al.	2019	BPMJ	Industry 4.0	Empirical	Digitalization transforms processes
6	Babina et al.	2024	JFE	Innovation & AI	Empirical	AI drives firm growth & innovation
7	Bag et al.	2021	JBR	Big data & AI	Survey	Institutional pressure affects adoption
8	Belhadi et al.	2022	AOR	AI in SCM	Empirical	AI improves supply chain performance
9	Bodendorf et al.	2022a	DSS	Data-driven SCM	Empirical	Data analytics improves decision-making
10	Bodendorf et al.	2022b	Electronic Markets	Procurement systems	Empirical	AI enhances procurement efficiency
11	Bokrantz et al.	2023	JMS	Maintenance	Empirical	AI supports predictive maintenance
12	Braganza et al.	2022	ISF	Workforce & AI	Empirical	AI impacts employment structures
13	Brintrup et al.	2020	IJPR	SC resilience	Empirical	Data analytics enhances resilience
14	Brintrup et al.	2023	PPC	AI in SCM	Empirical	AI integration challenges identified
15	Brynjolfsson et al.	2021	AEJ	Productivity	Empirical	J-curve effect of AI adoption
16	Budak & Sarvari	2021	ESA	Decision-making	Model	AI improves SC decisions

17	Burger et al.	2023	Procedia CIRP	Manufacturing	Empirical	AI adoption drivers identified
18	Calatayud et al.	2019	SCM IJ	Smart SC	Conceptual	Self-thinking supply chains
19	Cannas et al.	2023	JPSM	Procurement	Empirical	AI transforms procurement processes
20	Chatterjee et al.	2021	TFSC	AI adoption	Survey	Behavioral factors influence adoption
21	Chen et al.	2021	MISQ	Analytics	Conceptual	BI foundations for AI
22	Culot et al.	2020	IJPR	Industry 4.0	Review	Tech impacts on SCM
23	Culot et al.	2024	IJOPM	Digital SC	Empirical	Transformation strategies
24	Dalenogare et al.	2018	IJPE	Industry 4.0	Survey	Positive impact on performance
25	Demlehner et al.	2021	BISE	AI adoption	Empirical	Adoption challenges identified
26	Dey et al.	2023	JBR	Digital transformation	Empirical	AI enhances firm performance
27	Dolgui & Ivanov	2022	IJPR	Digital SC	Conceptual	AI-enabled SC design
28	Dora et al.	2022	TFSC	SMEs	Empirical	AI adoption barriers
29	Dwivedi et al.	2023	IJIM	AI research	Review	Future research directions
30	Feizabadi	2022	CIE	Inventory	Model	AI optimizes inventory control
31	Frank et al.	2019	IJPE	Industry 4.0	Empirical	Performance improvements
32	Gama & Magistretti	2023	R&D Mgmt	Innovation	Empirical	AI fosters innovation
33	Guida et al.	2023	PPC	SCM	Empirical	AI adoption insights
34	Gupta et al.	2022	IJPR	Resilience	Empirical	AI strengthens resilience
35	Hanelt et al.	2021	JMS	Digital transformation	Review	Organizational transformation
36	Hasija & Esper	2022	MSOM	AI SC	Empirical	AI reshapes operations
37	Helo & Hao	2022	Computers in Industry	Manufacturing	Empirical	AI improves SC efficiency
38	Hopkins	2021	PPC	Operations	Empirical	AI adoption drivers
39	Ji et al.	2021	TR Part E	Logistics	Empirical	AI improves logistics performance
40	Kinkel et al.	2023	JPSM	Reshoring	Empirical	AI supports reshoring
41	Kosasih & Brintrup	2022	IJPE	Risk	Empirical	Multi-tier SC risk analysis
42	Leoni et al.	2022	JMTM	Manufacturing	Empirical	Digital tech adoption
43	Merhi & Harfouche	2023	TFSC	Strategy	Empirical	AI leadership role
44	Modgil et al.	2022	AOR	Resilience	Empirical	AI improves adaptability
45	Mohiuddin et al.	2022	TFSC	Adoption barriers	Empirical	Key barriers identified
46	Olan et al.	2022	IJPE	Financial resilience	Empirical	AI improves resilience
47	Perano et al.	2023	JBR	Digital transformation	Review	Strategic insights

48	Perno et al.	2023	Computers in Industry	Configuration	Empirical	AI enables customization
49	Pozzi et al.	2023	PPC	Industry 4.0	Review	Tech classification
50	Rodríguez-Espíndola et al.	2022	IJPR	Blockchain & AI	Empirical	Integration benefits
51	Sodhi et al.	2022	POM	AI adoption	Empirical	Challenges in implementation
52	Wong et al.	2022	IJOPM	Logistics	Empirical	AI improves operations
53	Yadav et al.	2020	JCP	Sustainability	Empirical	AI supports green SCM
54	Zheng et al.	2023	RCIM	Federated learning	Empirical	Secure data sharing

Table A2. Methodology Classification

Methodology Type	Description	Frequency
Case Study	Firm-level empirical analysis	70
Survey	Questionnaire-based research	34
Mixed Methods	Combined qualitative & quantitative	8
Others	Secondary/archival analysis	11

Table A3. SCOR Process Coverage

SCOR Process	Description	Frequency
Plan	Forecasting, inventory	36
Source	Supplier selection	29
Make	Production optimization	58
Deliver	Logistics	18
Return	Warranty/returns	7
Enable	Integration & performance	52

Table A4. AI Techniques Used

AI Technique	Frequency
Random Forest	18
Neural Networks (ANN)	12
Linear Regression	12
Support Vector Machine	10
XGBoost	8
KNN	7
SVR	7
Others	49

Table A5. AI Purpose

Purpose	Frequency
Regression	26
Classification	15
Both	6
Clustering	2
Anomaly Detection	2

Table A6. Data Types Used

Data Type	Frequency
Production Data	30
Product Features	21
Demand Data	17
Sourcing Data	14
Machine Data	8
After-sales Data	3
Macroeconomic Data	3
Social Media Data	2