

Research Topic Identification of Supply Chains Empowered by Artificial Intelligence Technologies: Based on LDA Text Mining

Zhenyan Chen¹, Shaozeng Dong^{1*}, Jiaze Li²

1. School of Business, Jiangsu Ocean University, Lianyungang, Jiangsu, 222005, China

2. Business School, The University of Sydney, Sydney, NSW 2006, Australia

*Corresponding author: Shaozeng Dong, szdong@jou.edu.cn

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Abstract: Existing research on AI-empowered supply chains remains constrained by fragmented topic clustering, unclear value transmission mechanisms, and the absence of a holistic theoretical framework. Drawing on 4,635 English-language articles published between 2000 and 2026 in ABS 3-star and above journals indexed in the Web of Science Core Collection, this study applies LDA topic modeling to identify research topics and deconstruct empowerment dimensions. Following text preprocessing, the optimal number of topics ($K = 20$) is determined using perplexity metrics. Twenty core topics are identified and clustered into five empowerment dimensions: digital-intelligence optimization, chain-link operation, supply chain network (SCN) security, cross-border scheduling, and sustainable development. Social network analysis is then used to quantify topic correlations and value transmission paths, based on which a conceptual model of AI-empowered supply chains is developed. The findings show that AI empowers supply chains through these five clearly bounded dimensions, forming a closed-loop value-generation and dynamic feedback mechanism that links theoretical research with industrial practice. By integrating fragmented findings, this study deconstructs the field's core topics and empowerment dimensions and establishes a closed-loop interpretive framework. It clarifies how AI is transformed from a technical application into strategic supply chain value, offering theoretical references and practical implications for intelligent supply chain transformation.

Keywords: Artificial Intelligence; Supply Chain; LDA Model; Topic Identification; Conceptual Model; Text Mining

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1. Introduction

Amid the ongoing technological revolution and industrial transformation, artificial intelligence (AI), a general-purpose core technology of the digital economy era, provides critical impetus for digital and intelligent transformation across industries. AI is expected to generate USD 13 trillion in economic value by 2030 (Pournader et al., 2021). At the same time, global supply chains face intertwined external shocks, including escalating geopolitical tensions, shifting international trade landscapes, tightening dual-carbon constraints, and frequent extreme events. These shocks have altered the operating logic and governance models of traditional supply chains (Kareem et al., 2025). Regional industrial chain restructuring, rising trade protectionism, and frequent climate-related disasters, combined with stringent green and low-carbon transition requirements, have made supply chain disruptions increasingly routine. Systemic problems, such as supply-demand mismatches and high

operating costs, continue to surface. Severe supply chain disruptions have affected 70% of enterprises, causing average revenue losses of 15% and a marked decline in customer satisfaction (Riad et al., 2024). The conventional supply chain management paradigm based on experiential judgment struggles to adapt to a highly uncertain external environment. Supply chain governance objectives are no longer confined to operational efficiency; they now embrace a multi-value orientation that balances resilience building, intelligent collaboration, and sustainable development. Using intelligent technologies to address practical supply chain pain points and achieve end-to-end digital transformation has become an urgent industrial imperative. With technical advantages in demand forecasting, solution optimization, and risk prevention and control, AI serves as a critical technological foundation for supply chain upgrading and transformation.

Continued advances in artificial intelligence (AI) have established a solid technological foundation for the digital and intelligent transformation of supply chains. Spanning traditional machine learning and deep learning as well as emerging technologies such as generative AI, large language models, and knowledge graphs, these technologies can mitigate external disruptions to supply chains and enhance system stability, thereby supporting corporate sustainable development (Zhang & Zhang, 2025). In practice, supply chain uncertainty continues to intensify, management complexity rises substantially, and market demands for supply chain flexibility and agility keep growing. In this context, AI has become an essential instrument for addressing diverse supply chain disturbances (Singh & Modgil, 2025). As application scenarios continue to expand, academic research at the intersection of AI and supply chain management has grown rapidly. Research in this area covers demand forecasting, inventory optimization, logistics scheduling, risk management, green operations, and collaborative governance. Intelligent technologies, including machine learning, deep learning, and fuzzy logic, have been widely applied in these scenarios, making this a prominent frontier topic in operations management (Grover, 2025).

The application scope of artificial intelligence in supply chain management continues to expand, giving rise to a growing body of frontier interdisciplinary research. Current studies concentrate on demand forecasting, inventory optimization, logistics scheduling, risk management, green operations, and collaborative governance, with extensive discussion of intelligent technologies such as machine learning, deep learning, and fuzzy logic. These topics have become prominent research hotspots in operations management. Existing literature has examined AI-enabled supply chain development from multiple perspectives, including technical application, bibliometric analysis, theoretical construction, and value expansion. Nevertheless, the knowledge system in this field remains immature, leaving notable research gaps. Toorajipour et al. (2021), through a systematic literature review, catalogued mainstream technologies such as artificial neural networks and fuzzy logic, together with their application scenarios and practical effects in supply chains. However, their study offered only a fragmented inventory of technical functions, failing to deconstruct the field's overall knowledge logic or reveal the value-generation mechanism of technological empowerment, and thus lacking systematicity. Culot et al. (2024), drawing on an empirical literature review, concluded that the effective application of AI in supply chains depends on the coordination of multiple elements, including data, technology, organization, and strategy. Most existing studies, however, focus on single technologies or partial business scenarios and lack holistic theoretical frameworks that capture the closed-loop relationships among technology deployment, organizational integration, and performance output. Condé and Münch (2025) examined the empowering effects of intelligent technologies on green operations and social responsibility in supply chains, but their analysis was confined to the single dimension of sustainability. They did not conduct an integrated analysis covering efficiency improvement, resilience enhancement, and sustainable development, leaving the trade-offs and collaborative empowerment pathways among multiple objectives underexplored.

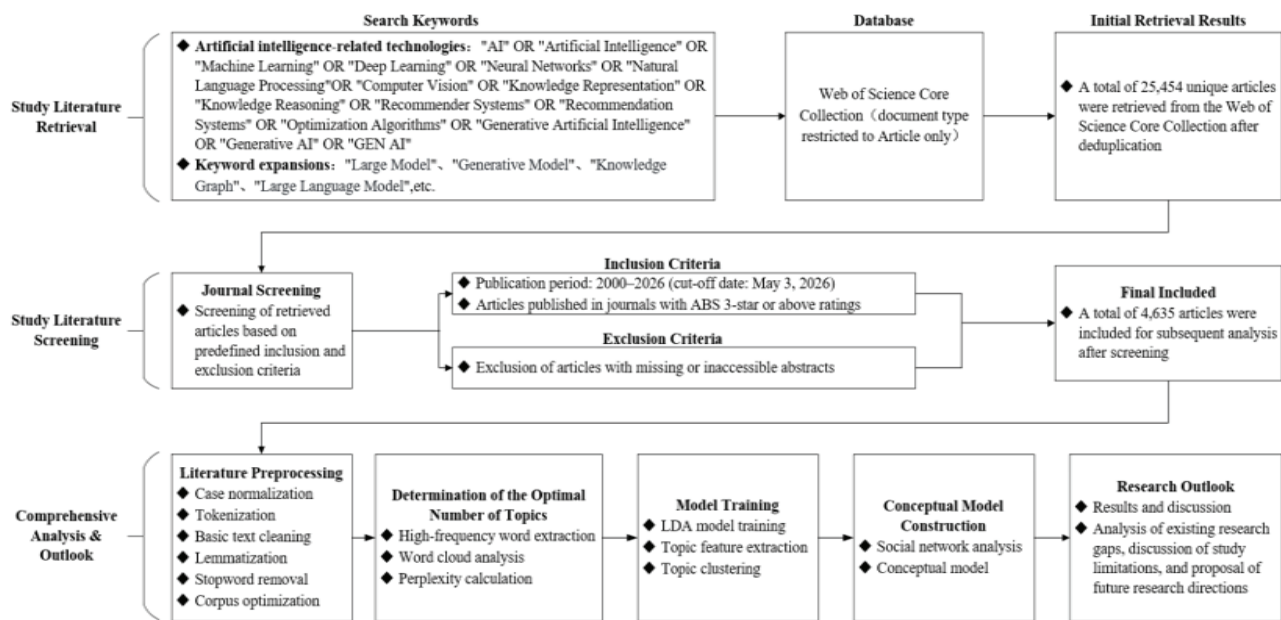
Overall, existing research in this field is characterized by pronounced fragmentation and scenario-specific limitations. Most studies focus on individual technologies or isolated supply chain links and adopt one-directional, linear analytical paradigms, without developing systematic topic clustering or a panoramic knowledge map. No unified, integrated theoretical framework has yet been established, substantially limiting the explanatory power and practical value of existing research for intelligent supply chain transformation.

2. Materials and Methods

This study employs the Latent Dirichlet Allocation (LDA) topic model for text mining and research hotspot identification

to systematically map evolutionary trends and core topics in AI-empowered supply chain research. LDA is a classic probabilistic topic model in natural language processing and is well suited to handling large volumes of unstructured textual data. It requires no predefined text structures or prior assumptions about sample distributions and does not rely on syntactic features, making it appropriate for research topic extraction. First introduced by Blei et al. (2003), LDA is a well-established automated text mining technique and has been widely applied across multiple fields, including public administration (Walker et al., 2019), business administration (George et al., 2016), and econometrics (Gentzkow et al., 2019). As an unsupervised probabilistic text mining tool, LDA requires no manual corpus labeling, accommodates large-scale text datasets, and delivers robust semantic recognition and interpretable outputs; its validity as a research method has been widely confirmed (Blei et al., 2003). Following standard LDA analytical procedures, this study proceeds in three stages: literature retrieval design, literature screening and preprocessing, and integrated analysis and result generation (see Figure 1).

Figure1: Research Flow Design. (ABS = Association of Business Schools)



2.1 Literature Retrieval Planning

Artificial intelligence (AI) enables machines to simulate human cognitive capabilities, including problem-solving and logical reasoning, and supports organizational operational optimization and business process automation. Its core technical scope encompasses machine learning, deep learning, neural networks, natural language processing, computer vision, knowledge representation and reasoning, recommender systems, and optimization algorithms. As a key branch of AI, generative AI can produce multimodal outputs—including text, images, audio, and video—based on machine learning models (Daio et al., 2025). Drawing on this technical definition, this study develops Boolean search queries combining core terms such as “AI,” “Artificial Intelligence,” “Machine Learning,” “Deep Learning,” “Neural Networks,” “Natural Language Processing,” “Computer Vision,” “Knowledge Representation,” “Knowledge Reasoning,” “Recommender Systems,” “Optimization Algorithms,” “Generative Artificial Intelligence,” “Generative AI,” and “GENAI,” supplemented by extended keywords including “Large Model,” “Generative Model,” “Knowledge Graph,” and “Large Language Model,” together with “Supply Chain.” A topic-oriented search was performed in Web of Science across titles, abstracts, keywords, and subject terms. The document type was limited to journal articles. After deduplication, 25,454 preliminary records were obtained.

2.2 Literature Screening

To ensure the authority and validity of the research sample, this study applied standardized inclusion and exclusion criteria to screen the initially retrieved literature. Papers without available abstracts were excluded. The inclusion criteria specified a publication window from 2000 to 2026, with May 3, 2026, as the cut-off date, and retained only articles published in ABS 3-star and above journals in business administration, logistics management, and technology management. After multiple rounds of systematic screening, 4,635 high-quality papers were finalized as the formal research sample.

2.3 Comprehensive Analysis

The analytical procedure comprises five steps. First, the Python Gensim library is used to perform standardized text preprocessing on article abstracts and to construct a dedicated corpus. Second, AntConc is employed for high-frequency word statistics and word cloud visualization, and the optimal number of topics ($K = 20$) is determined using perplexity metrics. Third, LDA model training and topic feature extraction are conducted, and the extracted topics are grouped into five empowerment dimensions: digital-intelligence optimization, chain-link operation, supply chain network security, cross-border scheduling, and sustainable development. Fourth, social network analysis is performed to interpret the correlation pathways among topics and dimensions, construct the conceptual model, and clarify the internal mechanisms underlying AI-empowered supply chains. Fifth, this study identifies existing research gaps, discusses its limitations, and proposes directions for future research.

3. Research Procedures

3.1 Assists

Results can be presented in tables or figures, with a particular emphasis on figures to improve reader accessibility. However, many straightforward findings may be presented directly in the text. Results should be clearly separated from the discussion, and it is recommended to avoid repeating results in the text that are already presented in figures or tables.

3.2 Literature Retrieval

This study employs a two-stage screening framework to ensure accurate sample selection. In the first stage, Boolean search strings are used to retrieve the initial literature, while non-academic outputs such as conference abstracts, book reviews, and news reports are excluded. After deduplication, 25,454 valid preliminary records are obtained. In the second stage, the inclusion and exclusion criteria described above are applied for further filtering, yielding a final sample of 4,635 articles for subsequent analysis.

3.3 Text Preprocessing

Text preprocessing is an essential prerequisite for corpus construction and model training. Preprocessing quality directly affects natural language processing performance and shapes both LDA model fit and text mining accuracy (Chai, 2023). Article abstracts serve as the analytical objects. Using Python 3.12, this study applies the NLTK toolkit to implement standardized text processing, covering case normalization, tokenization, basic text cleaning, lemmatization, stop-word removal, and corpus optimization, so as to standardize and refine the textual dataset.

The detailed preprocessing procedures are as follows:

- (i) Case normalization: All textual content is converted to lowercase to eliminate interference from case differences.
- (ii) Tokenization: Abstract texts are segmented into independent word units using the NLTK tokenizer.
- (iii) Basic text cleaning: URLs, email addresses, pure numeric characters, punctuation marks, and invalid special symbols are removed, and only alphabetic tokens are retained for subsequent analysis.
- (iv) Lemmatization: Combined with NLTK part-of-speech tagging and WordNet criteria, inflected words sharing the same root form are merged to reduce textual data variance and improve model stability.
- (v) Stop-word filtering: Two stop-word lists are adopted. The built-in English stop-word list of Gensim removes common function words such as “a”, “the”, and “an”. A custom stop-word list removes semantically empty terms, including “total”, “large number”, and “paper”, to reduce feature dimensionality and optimize model performance.
- (vi) Corpus optimization: Multi-word core concepts are standardized and unified. Specifically, “supply chain” and “sc” are uniformly replaced with “supplychain”, and “artificial intelligence” is replaced with “ai”, thereby further enhancing the overall quality of the processed corpus.

3.4 Word-cloud Analysis

As the basic unit of textual feature representation in natural language processing, vocabulary can objectively reflect the core research agenda and evolutionary trajectory of a given domain (Rafi et al., 2021). This study employs AntConc to extract high-frequency feature words from the preprocessed corpus and generates a weighted word cloud visualization (see Figure 2). The results reveal prominent high-frequency terms related to operations management, including management, decision,

optimization, performance, cost, and risk, alongside terms associated with typical supply chain nodes such as demand, inventory, logistics, supplier, production, and manufacturer. These patterns indicate that existing studies primarily focus on AI applications in key supply chain links, covering demand forecasting, inventory control, supplier collaboration, logistics scheduling, and production operation optimization. The frequent occurrence of terms such as firm, strategy, and process reflects sustained academic attention to corporate operations and strategic management. In addition, the high frequency of sustainability-related terms such as sustainability and environment indicates growing research interest in green development. Overall, the current research landscape is grounded in the application of technical models, focuses on end-to-end intelligent upgrading of supply chains, and pursues multiple developmental goals, including intelligent optimization, risk control, resilience enhancement, and sustainable development.

Figure 2: Word-cloud of the target literature corpus. (NLTK=Natural Language Toolkit)



3.5 Perplexity Analysis

Perplexity is a core evaluation metric in topic modeling analysis (Neishabouri & Desmarais, 2020). It measures model fit and predictive performance on unseen texts using text probability distributions. As a key indicator for selecting the optimal number of LDA topics, perplexity is widely used in academic literature mining, industrial text clustering, and research hotspot detection (Blei et al., 2003). Perplexity is negatively correlated with model generalization capacity: a lower perplexity value indicates that the learned semantic patterns better fit the original corpus, yield more robust topic partitioning, and deliver stronger predictive performance for unseen documents.

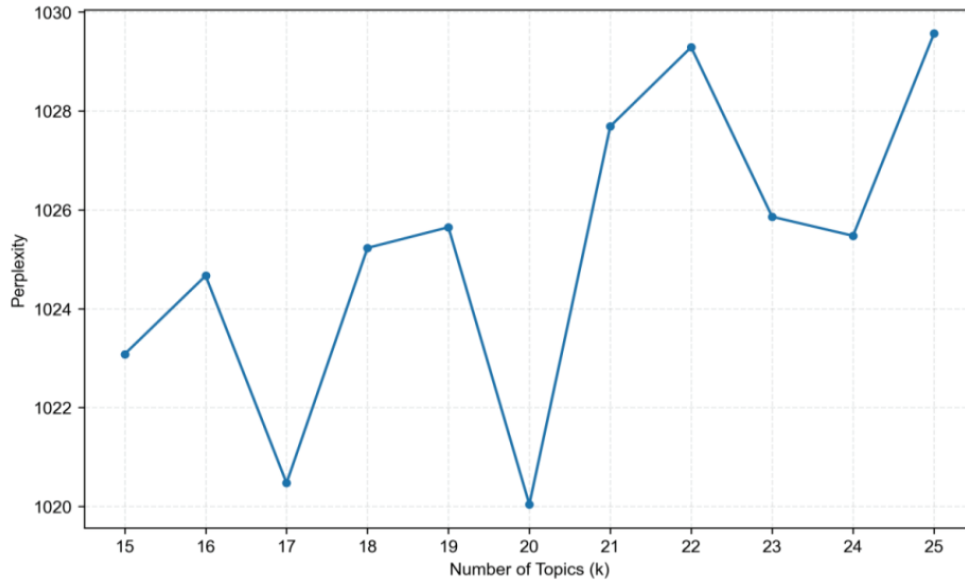
Perplexity formula:

$$Perplexity(D) = \exp\left(-\frac{\sum_{d=1}^M \log p(w_d)}{\sum_{d=1}^M N_d}\right) \quad (1)$$

Where D denotes the full corpus set; M represents total documents within the corpus; $p(w_d)$ denotes joint probability of document- d generated by LDA; N_d refers to valid token count after tokenization and filtering for document- d .

Calculations are performed via Python Gensim. Model iteration is set to 2000 epochs with 20 global passes. Topic numbers range from 1 to 20. Perplexity values are computed iteratively across different topic-number settings and plotted as a perplexity curve (see Figure 3). According to inflection-point characteristics of the curve, the optimal number of topics is determined as $K = 20$.

Figure 3: Perplexity Variation Curve



3.6 LDA Topic Modeling

Preprocessed corpora are imported into the Python LDA module for topic analysis. Three critical hyper-parameters govern LDA: α , β , and K . α controls smoothing of document-topic distributions; β characterizes smoothing of word-topic distributions. The corresponding log-likelihood function is written as:

$$l(\alpha, \beta) = \sum_{d=1}^M \log p(w_d | \alpha, \beta) \quad (2)$$

Smaller α values strengthen topic salience for individual documents; smaller β values enhance the associative strength between feature words and specific topics. Following recommendations from Blei et al. (2003), $\alpha=0.1$ and $\beta=0.1$ are adopted to generate semantically interpretable topics. Based on foregoing perplexity outputs, hyper-parameter K is set to 20.

After model training was completed, the output topic-feature word table was interpreted and topics were named, as shown in Table 1. Twenty research topics were identified and named based on the high-frequency feature words of each topic and the research context of existing relevant literature. T1, characterized by feature words such as spillover and country, corresponds to “Global Policy” (Pei et al., 2017); T2, containing terms including supplier and buyer, is named “Chain Node Selection” (Kellner et al., 2019); T3, revolving around inventory and production, is labeled “Inventory Optimization” (Sarker et al., 2014); T4, with retailer and manufacturer as its core feature words, is entitled “Production Pricing” (Terzi et al., 2025); T5, represented by emission and carbon, is designated “Green Development” (Shahzad et al., 2024); T6, covering food and disaster, is named “Anomaly Response” (Kayhan et al., 2024); T7, featured by collaboration and share, is labeled “Collaboration & Sharing” (Xu et al., 2024); T8, whose core terms are batch and package, is named “Picking & Packaging” with reference to prior studies (Cheng et al., 2015; Agrawal et al., 2019); T9, including supplychain and ai, is entitled “Digital Intelligence Operation” (Sun et al., 2025); T10, dominated by maintenance and network, is designated “Supply-Chain Network (SCN) Prevention & Control” (Qu et al., 2015); T11, containing trade and global, is named “Cross-border Trade” (Feng et al., 2025); T12, centering on supplychain and disruption, is labeled “Linkage Security” (Liang et al., 2025); T13, characterized by supplychain and performance, is entitled “Performance Evaluation” (Khan et al., 2019); T14, with transshipment and request as feature words, is named “Cross-border Allocation”; T15, including risk and averse, is designated “Risk Management & Control”; T16, taking model and algorithm as core terms, is labeled “Decision Optimization” (Lee et al., 2006); T17, containing remanufacturing and life, is named “Product Remanufacturing”; T18, whose feature words are supplychain and model, is entitled “Linkage Optimization”; T19, revolving around logistics and reverse, is designated “Reverse Logistics”; T20, dominated by forecast and model, is labeled “Model Prediction”.

Further topic-clustering analysis aggregated the above research topics into five enablement dimensions: cross-border scheduling, chain-link operation, digital-intelligence optimization, supply-chain network security, and sustainable

development. Detailed clustering outcomes are presented in Table 2.

Table 1. LDA Topic Analysis

Topic	Top10 feature words	Topic label
T1	spillover, country, policy, industrial, em, district, gscm, local, global, gvcs	Global Policy
T2	supplier, buyer, blood, supply, selection, source, trust, gsc, communication, criterion	Chain Node Selection
T3	inventory, production, product, cost, time, demand, policy, level, model, optimal	Inventory Optimization
T4	retailer, manufacturer, price, market, consumer, product, profit, platform, cost, channel	Production Pricing
T5	emission, carbon, environmental, energy, sustainable, green, economic, policy, production, economy	Green Development
T6	food, waste, disaster, agricultural, relief, agriculture, biomass, alliance, recycle, harvest	Anomaly Response
T7	collaboration, share, procurement, resource, knowledge, enterprise, ontology, exchange, negotiation, leakage	Collaboration & Sharing
T8	batch, package, pick, commitment, cp, hedge, drug, motor, french, zone	Picking & Packaging
T9	supplychain, ai, data, firm, technology, management, performance, model, capability, business	Digital Intelligence Operation
T10	failure, container, maintenance, cascade, job, network, node, repair, attack, probability	SCN Prevention & Control
T11	trade, global, country, port, export, sector, international, input, china, regional	Cross-border Trade
T12	supplychain, disruption, resilience, risk, network, supply, pandemic, covid, event, climate	Linkage Security
T13	supplychain, firm, performance, finance, financial, relationship, capital, smes, service, enterprise	Performance Evaluation
T14	transshipment, request, steel, reshoring, offshore, cod, lateral, picker, da, army	Cross-border Allocation
T15	risk, averse, hydrogen, measure, carrier, aversion, pull, labour, tax, push	Risk Management & Control
T16	model, algorithm, cost, solution, supplychain, network, solve, decision, program, time	Decision Optimization
T17	remanufacturing, hospital, farm, farmer, patient, remanufactured, life, impact, medical, health	Product Remanufacturing
T18	supplychain, model, process, decision, product, agent, manufacture, performance, management, method	Linkage Optimization
T19	logistics, service, online, reverse, customer, provider, credit, stream, task, live	Reverse Logistics
T20	forecast, data, learn, demand, model, accuracy, prediction, machine, method, predict	Model Prediction

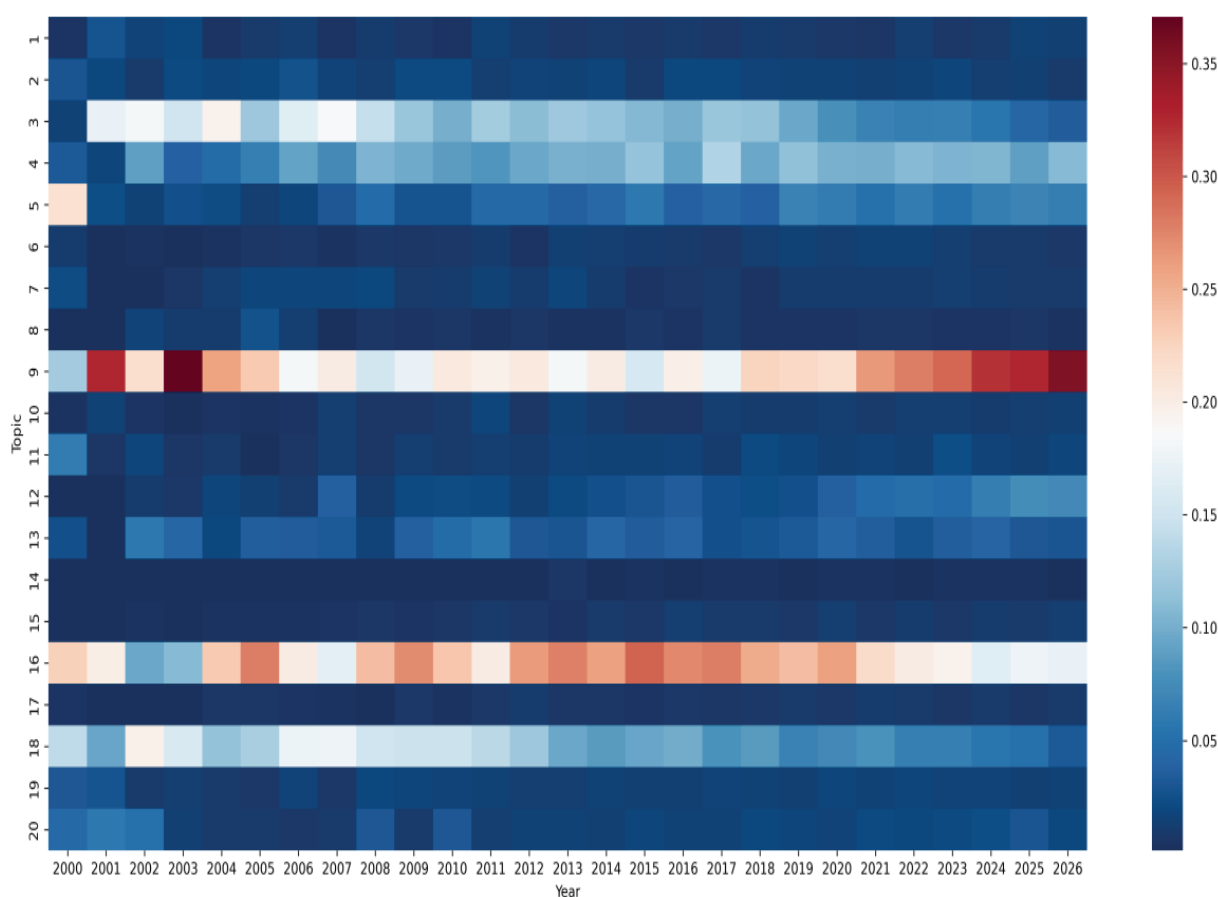
Abbreviations: LDA, Latent Dirichlet Allocation; gscm, green supply chain management; gvcs, global value chains; gsc, green supply chain; smes, Small and Medium Enterprises;

Table 2. LDA Topic Clustering

Cluster	Included topics	Dimension
C1	T1, T11, T14	Cross-border Scheduling
C2	T2, T4, T7, T8, T13	Chain-link Operation
C3	T3, T9, T16, T18, T20	Digital-intelligence Optimization
C4	T6, T10, T12, T15	Supply-chain Network Security
C5	T5, T17, T19	Sustainable Development

As shown in Figure 4, the heatmap visualizes the temporal evolutionary patterns of LDA topics. Color gradients reflect temporal shifts in research focus and illustrate evolutionary trajectories and stage-specific hotspots. Digital-intelligence optimization consistently constitutes the primary research thread in this field. Topic T9 maintains research popularity across the entire observation window: its publication share rises continuously after 2001, peaks during 2003–2004, and remains persistently high, representing the most sustained hotspot in the corpus. Characterized by core tokens such as “AI”, “data”, and “technology”, T9 demonstrates the deepening deployment of digital-intelligence technologies in supply chain management and the emergence of mainstream research paradigms. Within the same dimension, T16 retains high popularity between 2000 and 2018, representing early-to-mid-stage explorations of algorithm-driven supply chain decision-making. T3 forms a phase-specific hotspot from 2003 to 2008, after which its relative importance gradually declines and is superseded by comprehensive digital-intelligence operation topics. This suggests that supply chain optimization research is shifting from partial-link optimization toward holistic end-to-end digital-intelligent reconstruction. Within the supply chain network security dimension, T12 gains growing attention after 2008 and surges after 2020, reflecting growing scholarly interest in supply chain resilience and risk management amid multiple external shocks. Chain-link operation represents a foundational and sustained research stream. T4 and T13 have maintained medium popularity since 2001 as stable research themes in supply chain operations and performance evaluation. In summary, AI-empowered supply chain research revolves around digital-intelligence optimization and drives the iterative upgrading of supply chains toward higher efficiency, cost reduction, and sustainability.

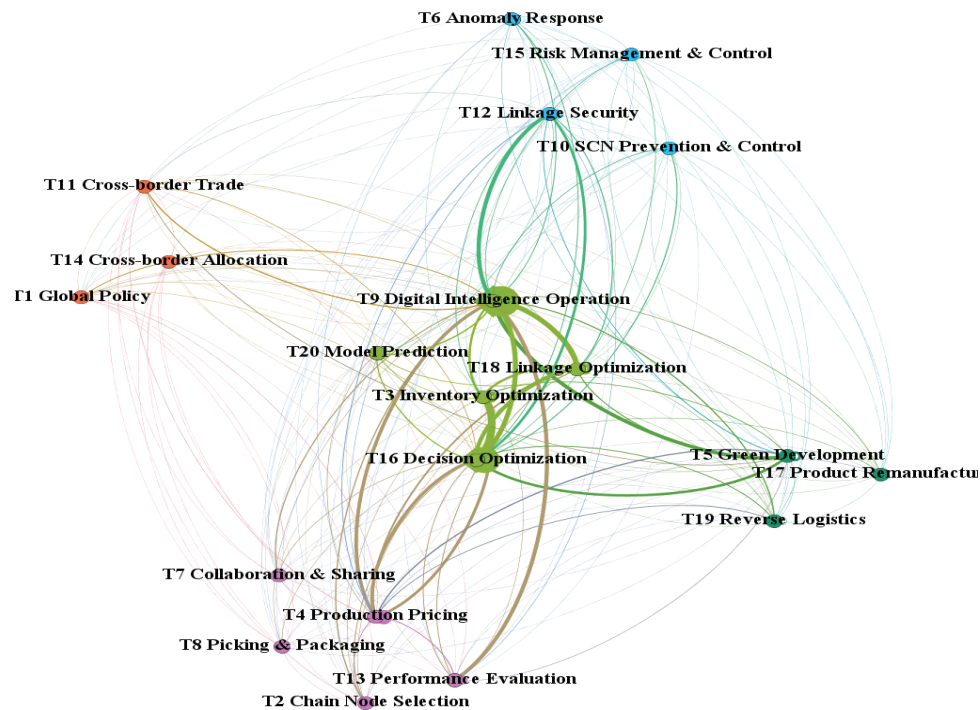
Figure 4: Temporal-evolution heatmap of LDA research topics.



3.7 Social Network Analysis

Social network analysis is an important bibliometric analytical tool (Lai et al., 2025). Based on topic co-occurrence matrices, an undirected weighted social network graph is constructed (Figure 5) to examine association patterns and cross-topic knowledge integration. Higher edge weights indicate more frequent co-occurrence and stronger knowledge integration between paired topics.

Figure 5: Co-occurrence social-network diagram of research topics



The network analysis reveals pronounced hierarchical differentiation among the 20 topic nodes. The strongest linkage occurs between T3 and T16, indicating that their co-occurrence dominates research output and constitutes a long-standing core focus of the field. T9 and T16 also exhibit high node strength, confirming the central position of Digital Intelligence Operation and Decision Optimization within the broader Digital Intelligence Optimization dimension. The close connection between T5 and T9 indicates that Green Development research is a vital component of digital-intelligence operation studies. Strong associations between T9–T12 and T9–T13 further suggest that linkage security and performance evaluation serve as core criteria for assessing the practical implementation outcomes of digital-intelligence technologies. In contrast, low-weight edges, such as T14–T17, T8–T14, and T14–T15, reflect limited accumulated research on the corresponding topics, which are classified as emerging and peripheral agendas.

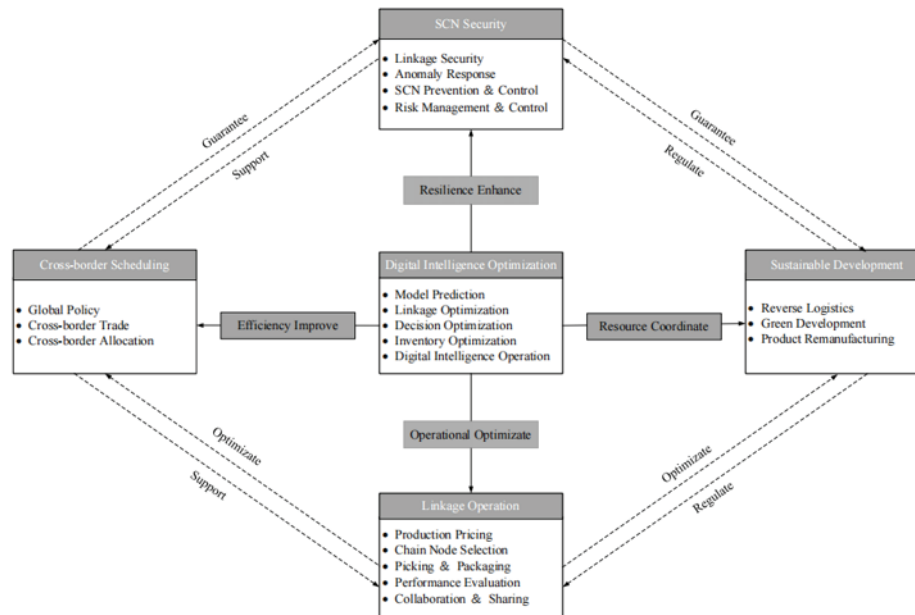
Overall, the network topology exhibits a clear core–periphery hierarchical structure in AI-empowered supply chain research. Cluster C3 constitutes the absolute core of the network and maintains dense connections with all other dimensions, serving as the primary driving force for disciplinary development. Clusters C2 and C4 establish robust linkages with C3 and represent the major practical application scenarios for digital-intelligence technology deployment. Although C1 and C5 exhibit relatively weak association intensity with the core layer, they sustain stable knowledge transmission pathways and thus represent promising avenues for future exploration. This identified network structure provides robust quantitative evidence for explaining value transmission pathways and multidimensional synergy mechanisms within AI-empowered supply chain systems.

4. Results and Discussion

Integrating LDA topic modeling and social network analysis, this study analyzes 4,635 high-quality articles published between 2000 and 2026 in ABS 3-star and above journals indexed in the Web of Science. It systematically deconstructs the core research topics, dimensional architecture, and internal correlation mechanisms of AI-empowered supply chains. Through perplexity analysis, twenty optimal research topics are identified and further clustered into five empowerment dimensions: digital-intelligence optimization, linkage operation, supply chain network security, cross-border scheduling, and sustainable development. Drawing on the core–periphery structural features revealed by social network analysis, a multi-layered conceptual model of AI-empowered supply chains is constructed (Figure 6). The findings demonstrate that AI-driven supply chain empowerment is not merely a simple linear superposition of technological, operational, and strategic factors. Instead,

it represents a complex closed-loop system formed through the dynamic coupling of multidimensional components. The synergistic interaction of these elements is critical to realizing the value generated by intelligent technologies.

Figure 6: Conceptual Model of Supply Chains Empowered by Artificial-intelligence Technologies



4.1 Core: Digital-intelligence Optimization

The Digital Intelligence Optimization dimension (C3) occupies a central position in the conceptual model. It serves as the technical core and primary driver of AI-empowered supply chain systems, encompassing five key research themes: Inventory Optimization (T3), Digital Intelligence Operation (T9), Decision Optimization (T16), Linkage Optimization (T18), and Model Prediction (T20). Social network analysis reveals that C3 maintains high-intensity connections with the other four dimensions, exhibiting larger node sizes and higher edge weights than the other four. These findings confirm that digital intelligence technologies have permeated the full operational workflow of supply chains and form the fundamental technological foundation of AI-empowered supply chain systems.

(1) Model Prediction and Decision Optimization. Model prediction (T20) and decision optimization (T16) constitute core components of digital-intelligence optimization. Their highest co-occurrence weight indicates a deep integration of data-driven precise forecasting with operational-strategy optimization. Machine-learning-based predictive analytics supports demand anticipation, inventory calibration, and production-scheme iteration, thereby simultaneously improving supply chain operational efficiency and cost control (Audibert et al., 2023). T16 maintained high scholarly attention during 2000–2018, representing early-to-mid-stage explorations that applied linear programming and heuristic algorithms to inventory scheduling and logistics path planning. By contrast, scholarly interest in T20 has risen continuously since 2015. Driven by iterative advances in machine learning and deep learning, data-intensive precise supply chain forecasting has evolved into an emerging research frontier.

(2) Digital-intelligence Operation. Digital-intelligence operation (T9) represents the most enduring hotspot in the corpus. Its popularity grew continuously after 2001, peaked in 2003–2004, and has remained persistently high. Feature words such as “AI,” “data,” “technology,” and “capability” reflect the expanding scope and depth of digital-intelligence technology deployment in supply chain management. Early scholarship focused on efficiency gains in isolated supply chain links, such as economic order quantity models and safety inventory calculation. With advances in big data and cloud computing, research priorities shifted toward holistic end-to-end digital-intelligent operations covering procurement, production, logistics, and sales. Leveraging strengths in data perception, real-time analytics, and intelligent execution, AI breaks down data silos across supply chain links, enables end-to-end information sharing and collaboration, and systematically reconstructs traditional supply chain operation paradigms.

(3) Linkage Optimization. Linkage optimization (T18) addresses dynamic supply chain adjustment and resource allocation,

with representative feature words including “process,” “decision,” “agent,” and “manufacture.” Conventional supply chain risk assessment and optimization models are often built on static assumptions, resulting in disconnection between prediction and decision modules and poor adaptability to volatile real-world supply chain contexts (Gao & Zhao, 2026). Powered by techniques such as multi-agent reinforcement learning, AI enables dynamically adaptive supply chain regulation, copes with market demand volatility and external environmental disturbances, and comprehensively enhances overall supply chain operational performance (Liu et al., 2025).

4.2 Chain-link Operation and Supply-chain Network Security

Chain-link operation (C2) and supply-chain network security (C4) act as critical hubs connecting core-layer digital-intelligence empowerment and practical supply-chain value realization. Chain-link operation delivers real-world technical deployment and directly determines operational efficiency and implementation outcomes of empowerment. Supply-chain network security establishes protective barriers for stable supply-chain functioning and provides resilience-oriented safeguards for value transformation.

(1) Chain-link Operation. Chain-link operation (C2) encompasses full-process supply chain activities, including supplier selection, production and sales pricing, logistics distribution, and performance evaluation. Social network analysis reveals strong correlations between C2 and the core cluster C3, as evidenced by the high co-occurrence intensity of topic pairs T3–T4 and T9–T13. This finding indicates that hybrid intelligence technologies can be embedded into supply chain strategic decision-making, improving demand forecasting accuracy and inventory management efficiency. Specifically, time-series models and machine learning algorithms used for intermittent demand prediction and dynamic replenishment threshold calibration can reduce inventory estimation bias and optimize inventory turnover (Singh et al., 2024). These results confirm the deep penetration of digital-intelligence technologies into routine supply chain operations and decision-making.

At the thematic level, chain node selection (T2) and production–sales pricing (T4) constitute fundamental operational procedures in supply chain management. AI enables multidimensional data mining and analytical processing, supporting precise supplier evaluation and selection and scientifically optimized production and sales pricing strategies. The close connections between picking and packaging (T8) and other topics further indicate that intelligent technologies can reduce manual operational errors and improve the transparency and standardization of logistics sorting workflows (Kumar et al., 2021).

Notably, the high-frequency keyword “SMEs” extracted from the performance evaluation theme (T13) corroborates the conclusions of Patil et al. (2024), who suggested that hybrid intelligence technologies substantially empower production scheduling optimization in small and medium-sized enterprises (SMEs). Despite this potential, the practical implementation of digital and AI-enabled solutions in SMEs is often constrained by tangible barriers, including insufficient resource endowments, inadequate infrastructure, and limited managerial and organizational support (Dassouli et al., 2024). Existing research on intelligent supply chains predominantly focuses on large core enterprises, while SMEs generally lag in digital and intelligent transformation due to shortages of capital, technology, and professional talent. Accordingly, developing low-cost, lightweight, and easily deployable intelligent tools through the technological spillover of leading enterprises to address the operational weaknesses of SME supply chains represents a critical and urgent direction for future practice-oriented research.

(2) Supply-chain Network Security. The supply chain network security dimension (C4) focuses on external shock identification, risk resistance, and system recovery, addressing supply chain stability risks in complex and volatile operational environments. Temporal evolution analysis shows that scholarly attention to linkage security (T12) has steadily increased since 2008 and surged after 2020. This trend indicates that building supply chain resilience has become a core strategic priority for both academia and industry, amid escalating geopolitical tensions, recurrent public health emergencies, and frequent extreme climate disturbances.

The strong correlations between linkage security (T12) and topics related to sustainable development confirm that AI and big data technologies enable enterprises to cope with supply chain disruptions and achieve coordinated improvements in resilience and sustainability (Trabucco & De Giovanni, 2021). Specifically, supply chain network prevention and control (T10) focuses on identifying vulnerabilities in complex supply chain networks, while risk management and control (T15)

emphasizes quantitative risk assessment and early risk anticipation. Integrating complex network theory with intelligent algorithms enables the identification of critical nodes and vulnerable links, the simulation of risk propagation paths and impact scopes, and evidence-based proactive risk governance for supply chain systems.

In contrast, the weak association between cross-border resource allocation (T14) and risk management and control (T15) points to a notable research gap in risk transmission mechanisms and intelligent scheduling optimization for transnational and cross-regional supply chain scenarios. This subdomain remains understudied, with considerable potential for future research.

4.3 Cross-border Scheduling and Sustainable Development

Although cross-border scheduling (C1) and sustainable development (C5) exhibit relatively weak linkage intensity with the core digital-intelligence optimization layer, they maintain stable knowledge transmission pathways. These two dimensions thus serve as critical outward extensions of AI-empowered supply chain frameworks and represent emerging frontier directions for future academic research and industrial practice.

(1) Cross-border Scheduling. The cross-border scheduling dimension (C1) addresses cross-regional collaborative operations and optimal resource allocation amid the ongoing restructuring of global supply chain patterns. The accelerating regionalization and fragmentation of global supply chains, coupled with intensified geopolitical frictions, rising trade protectionism, and regulatory updates concerning the Carbon Border Adjustment Mechanism, have imposed complex operational constraints and volatile risk disturbances on cross-border supply chain systems. Global policy (T1) and cross-border trade (T11) investigate how macro-level factors, including international trade rules, tariff barriers, and regional economic integration, reshape the spatial layout and operational mechanisms of cross-border supply chains. Artificial intelligence can synthesize multi-source heterogeneous data covering trade policies, logistics lead times, exchange rate fluctuations, and regional regulatory requirements, thereby providing intelligent decision support for enterprises in cross-border strategic layout, resource allocation, and risk mitigation.

As the core thematic component of C1, cross-border allocation (T14) exhibits weak linkages with other research topics and suffers from insufficient cumulative research and immature theoretical frameworks, constituting a notable research deficiency in the current domain. Future studies should prioritize the development of multi-constraint intelligent scheduling models for cross-border supply chains. By incorporating multidimensional constraints such as tariff variations, logistics lead times, carbon emission regulations, and geopolitical risks, such models can support the dynamic optimization of cross-border transportation routes and transnational inventory deployment. Additionally, further research is needed to construct resilient global supply chain networks and develop collaborative adaptation mechanisms that balance global deployment with regional clustered production, thereby enhancing the anti-interference capability and dynamic adaptability of cross-border supply chain systems.

(2) Sustainable Development. The sustainable development dimension (C5) addresses the dual environmental and social responsibility goals of supply chains while exploring intelligent empowerment pathways for green, low-carbon, and sustainable operational transformation. Social network analysis reveals high co-occurrence weights between green development (T5) and digital-intelligence operation (T9). This finding confirms that AI technologies not only enhance the operational efficiency of supply chain systems but also address practical challenges in green operations and sustainable governance, thereby enabling bidirectional synergy between efficiency-oriented optimization and green-oriented empowerment (Arkeman et al., 2023).

5. Conclusions and Implications

5.1 Main Conclusions

Based on 4,635 peer-reviewed articles retrieved from Web of Science and published in ABS 3-star and above journals between 2000 and 2026, this study employs LDA topic modeling, temporal evolution analysis, and social network analysis to systematically delineate the evolutionary trajectories of AI-empowered supply chain research. It identifies fine-grained research topics, clarifies the correlational structures among thematic clusters, and constructs a multi-layered conceptual framework encompassing five core dimensions: digital-intelligence optimization, chain-link operation, supply chain network security, cross-border scheduling, and sustainable development. The key findings are summarized as follows.

First, AI-empowered supply chain research comprises 20 well-defined and relatively independent fine-grained topics, which are hierarchically clustered into the five empowerment dimensions identified above. These dimensions constitute a complete empowerment system covering the full research scope, from underlying technical applications and operational implementations to risk resilience assurance, cross-border resource allocation, and green value extension.

Second, the field exhibits a typical core–periphery network structure. Digital-intelligence optimization occupies the core position of the entire empowerment system and serves as the fundamental driver of the intelligent transformation of modern supply chains. Chain-link operation and supply chain network security function as critical practical hubs, translating digital-intelligence empowerment into tangible operational improvements and effective risk prevention mechanisms. By contrast, cross-border scheduling and sustainable development represent peripheral and extended research directions. Although they maintain stable knowledge connections with the core layer, relevant research accumulation remains insufficient, leaving substantial room for further exploration.

Third, temporal evolutionary trajectories indicate that digital-intelligence optimization has consistently dominated the research agenda in this domain. The overall research focus has gradually shifted from isolated single-link optimization toward holistic end-to-end systemic reconstruction. Moreover, scholarly attention to supply chain resilience and risk governance has surged since 2020, driven by growing emphasis on supply chain security governance amid frequent external shocks. Cross-border collaboration and green sustainability research remain in an emergent stage, with considerable potential for future research.

Fourth, AI-enabled supply chain empowerment cannot be regarded as a simple linear superposition of technological, operational, and strategic elements. Instead, it forms a sophisticated closed-loop system characterized by dynamic coupling and interactive relationships across the five dimensions. The value realization of digital-intelligence relies on practical operational scenarios, resilience-oriented risk safeguard mechanisms, and long-term sustainable development guidance. Accordingly, multidimensional synergistic interactions are an essential prerequisite for the successful intelligent upgrading and transformation of supply chain systems.

5.2 Practical Implications

(1) Enterprise-level Implications. From a practical corporate perspective, the implementation of AI-driven supply chain transformation extends beyond algorithmic and technical solutions. It requires the effective integration of industry-specific experiential knowledge, cross-functional collaboration, and systematic internal skill training within organizations (Krzywdzinski, 2022). Firms should therefore avoid over-reliance on purely technical tools at the expense of the organizational preconditions essential for intelligent supply chain upgrading. A progressive, step-by-step paradigm is preferable—one that consolidates foundational capabilities before large-scale implementation and then expands innovative applications—rather than pursuing indiscriminate full-chain intelligent renovation.

First, enterprises should solidify foundational digital-intelligence optimization capabilities. They need to address deficiencies in supply chain digital infrastructure, strengthen internal data governance, and eliminate data silos across procurement, production, warehousing, and logistics. By deploying advanced algorithmic tools for demand forecasting, inventory optimization, and intelligent decision-making, firms can gradually shift from isolated single-link optimization to systematic, end-to-end digital and intelligent governance.

Second, firms should pursue targeted technological enablement focused on chain-link operation and supply chain network security. AI technologies can be embedded into core business workflows, including supplier evaluation and selection, production and sales pricing, and warehouse picking management, thereby substantially improving operational efficiency. Simultaneously, greater emphasis should be placed on supply chain risk early warning and resilience enhancement. Intelligent network analysis tools can help identify vulnerable supply chain nodes, formulate systematic response mechanisms against external shocks, and achieve a dynamic balance between digital efficiency improvement and supply chain operational security.

Third, after establishing mature foundational digital capabilities, enterprises can extend intelligent applications to cross-border collaboration and green sustainability. Multinational corporations can adopt intelligent scheduling models to optimize

cross-border supply chain layout and transnational resource allocation. All firms should explore AI-enabled approaches to carbon footprint tracking and low-carbon operational management, reconciling economic profitability with sustainable green development goals. Furthermore, leading chain enterprises can generate technological spillover effects by developing lightweight, low-cost, and easily deployable intelligent tools, thereby facilitating the digital upgrading of upstream and downstream SMEs and narrowing the digital development gap within industrial supply chains.

(2) Government-level Implications. First, governments should expand policy support for basic technological research on AI applications in supply chain systems. Promoting industry–university–research collaboration is essential to achieving breakthroughs in core technologies, including supply chain forecasting algorithms, multi-agent collaborative scheduling, and risk simulation modeling. Such efforts can accelerate the scalable implementation of AI across diverse supply chain scenarios. Second, targeted policy interventions should be formulated to address the digital transformation challenges facing SMEs. Governments can launch inclusive digital support programs tailored to small and medium-sized enterprises, reducing their costs of accessing intelligent analytical and operational tools. These policies can address deficiencies in SME supply chain intelligence and facilitate coordinated digital upgrading across entire industrial chains.

Third, the institutional governance framework for intelligent supply chain development should be improved. Authorities should accelerate the development of unified industry standards for supply chain data sharing, data security regulation, and algorithm application norms. By refining legal and regulatory systems, policymakers can foster a robust industrial ecosystem for intelligent supply chains characterized by innovation-driven development, operational security, multi-stakeholder collaboration, and low-carbon green empowerment.

5.3 Future Research Directions

Future research on AI-empowered supply chains can advance along several directions suggested by the topic-evolution patterns and network gaps identified above. In cross-border supply chains, the weak linkage between cross-border allocation and risk management and control points to the need for intelligent optimization under multidimensional constraints—geopolitical risks, shifting trade policies, and carbon-border regulations—along with resilience-oriented network design and collaborative mechanisms that reconcile regional and global arrangements. SME-led supply chains also merit closer attention, given that existing literature remains skewed toward large core enterprises; research could explore lightweight AI solutions for resource-constrained firms, transformation mechanisms under resource scarcity, and technology spillovers within industrial chains. The intersection of AI and green supply chains warrants deeper integration, particularly AI-driven full-life-cycle carbon management, intelligent optimization algorithms for low-carbon operations, and the coordinated development of green and resilient supply chains under dual-carbon goals. Beyond partial-link optimization, future studies could investigate fully adaptive closed-loop systems powered by multi-agent and deep learning technologies—systems capable of autonomous perception, dynamic decision-making, and real-time adjustment—thereby moving AI-supply-chain research from instrumental application toward systemic reconstruction.

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Conflict of Interests

The authors declare that there is no conflict of interest regarding the publication of this paper.

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