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REVIEW

AI-Based Intelligent Supply Chains: Theoretical Exploration and Prospects*

SONG Hua[a]

Abstract

With the emergence of artificial intelligence (AI), supply chains are transitioning from traditional operating models to intelligent and data-driven systems. An AI-based intelligent supply chain is an advanced integrated technology and management system built on AI and machine learning, which achieves intelligence, networking, collaboration, integration, and automation. By combining human expertise with machine capabilities, these supply chains are evolving into autonomous systems that are capable of self-awareness, self-direction, and self-optimization, with resilience and sustainability as their objectives. AI-based intelligent supply chains increasingly depend on AI and machine learning to automate decision-making processes. By integrating advanced technologies such as AI, the Internet of Things, and big data, these systems are able to monitor and analyze each link of the supply chain in real time and promptly detect emerging issues and risks. The effectiveness of these systems hinges on development on both the supply and demand sides. On the supply side, organizational structure, process integration, and the coordination of key elements form the foundation for effective use of AI. On the demand side, users' cognitive, emotional, and functional recognition regarding AI are central determinants of its actual effectiveness. Ultimately, it is the alignment between supply and demand that shapes the performance of AI-based intelligent supply chains. The governance of these systems requires a hybrid approach that seamlessly integrates contractual, relational, and algorithmic mechanisms, with the extent of each varying by context.

Keywords artificial intelligence (AI); AI-based intelligent supply chain; supply and demand perspectives; hybrid governance mechanism; theoretical exploration and prospects

1 Introduction

As digital technology continues to develop and has been widely applied, the digitalization of supply chains has become a key driver for promoting high-quality industrial development (Pan, 2023; Weerabahu et al., 2023). Among these disruptive technologies—including blockchain, the Internet of Things (IoT), and cloud computing—the most striking is artificial intelligence (AI). By simulating human intelligence, AI enables computer systems to perform tasks similar to human thought and decision-making (Schutzer, 1990). AI spans various fields, including machine learning, natural language processing, and computer vision. It can improve its own

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[a] Business School, Renmin University of China, Beijing 100872, China

performance through learning and adaptation to make corresponding decisions based on the changes in the environment and tasks. The goal of AI is to enable computers to understand, reason, learn, and solve problems, as well as to interact and collaborate with humans. It is because of these characteristics that AI has been widely used in all aspects of business management, including marketing (Verma et al., 2021), strategic decision-making (Trunk et al., 2020), and credit risk management (Bussmann et al., 2021). Among these, supply chain management is a critical area for AI applications, which has driven the supply chain into a new stage (Ganesh & Kalpana, 2022; Toorajipour et al., 2021).

The integration of AI technology with supply chain operations and management is rooted in the pursuit of the value of supply chain digitalization. In today's increasingly complex supply chain environment, digital transformation has become an inevitable trend (Büyüközkan & Göçer, 2018). First, from a technical perspective, the digital supply chain is an intelligent best-practice system that relies on powerful data processing capabilities and excellent management of coordination and communication among hardware, software, and networks, thereby enabling the effective application of digital technology in supply chain management and operations. Second, at the behavioral level, the digital supply chain can promote interaction among organizations by reducing the costs of communication, coordination, and collaboration, thus improving interaction efficiency and achieving more efficient collaboration. Finally, in terms of outcomes, the digital supply chain, by providing more valuable, more accessible, and reasonably priced services, ensures consistent results and facilitates an intelligent network for human-computer interaction. This not only improves service quality but also provides more convenient services, ultimately delivering substantial values to all participants. AI is pivotal in achieving these goals, which makes the supply chain more accurate, agile, and efficient (Toorajipour et al., 2021).

Although AI applications have driven significant transformations in supply chain operations and management, and both the academic and business communities hold high expectations on the integration of AI with the supply chain, there are still some issues that require further analysis and exploration. These include the similarities and differences between AI-based supply chain operations and management and previous information-based supply chains or those based on other digital technologies, what the key factors are for AI-based intelligent supply chain operations and management to truly achieve high performance, and what the governance mechanism for the AI-based intelligent supply chain is, among others.

2 The Evolution of Supply Chains and Their Integration with AI

To understand the integration of the supply chain and AI, it is essential to consider the historical development of supply chain operations and management, as well as the corresponding advancement of information technology (see Figure 1). In fact, the concept of the supply chain has undergone a continuous development process (Song, 2023), evolving from 1.0 to 5.0.

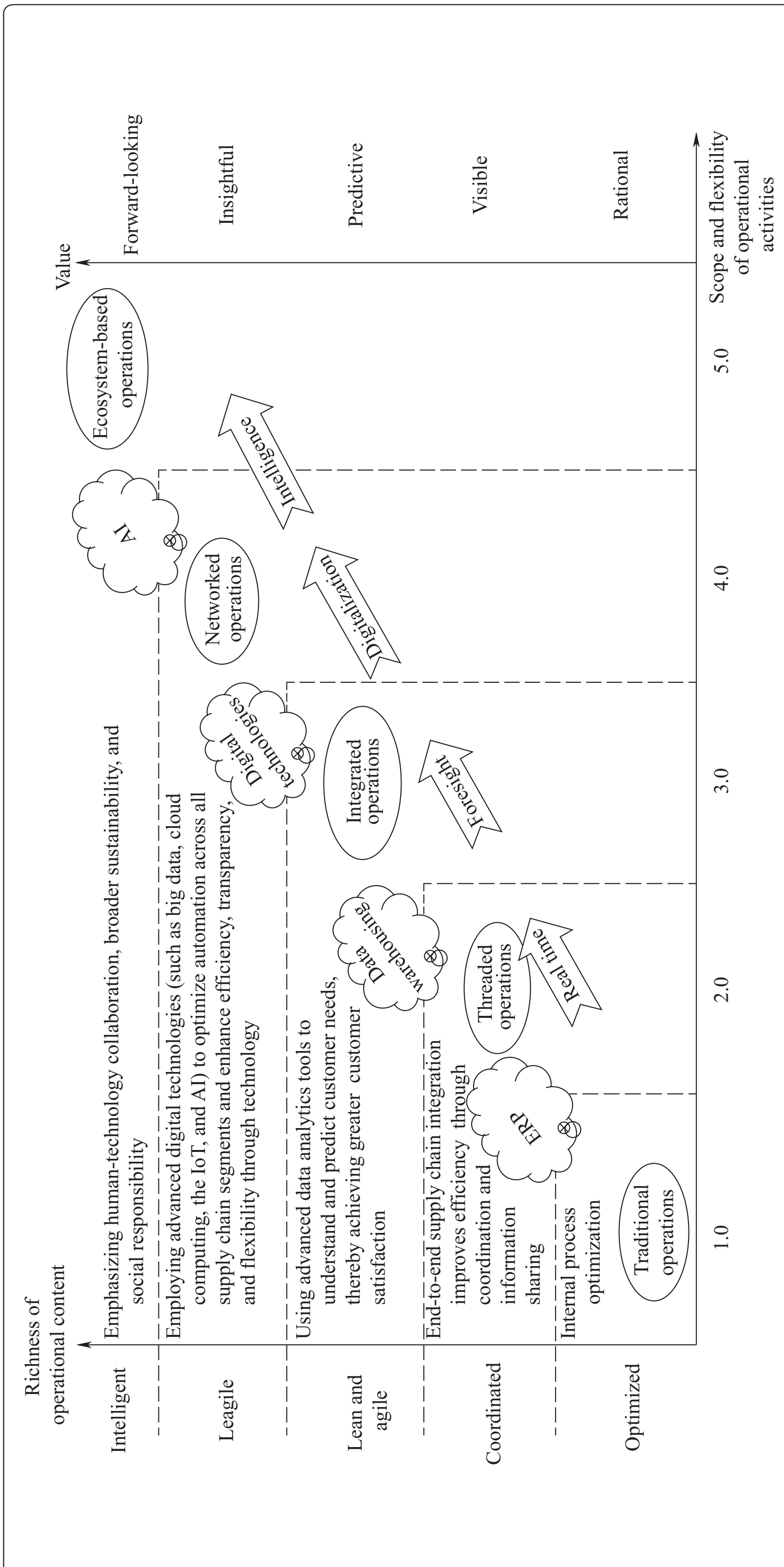

Figure 1 Evolution of the Supply Chain

The concept of the supply chain emerged in the late 1970s and early 1980s, when supply chain management became a major subfield within management studies. This evolution was driven by two major factors. First, as the market economy shifted its focus from the supply side to the demand side, the quality and effectiveness of economic development increasingly depended not only on producers but also on markets and customers. For enterprises, the ability to quickly and accurately understand market conditions and customer needs, and to guide procurement, production, and logistics accordingly, became essential for overcoming fragmented, siloed decision-making and was central to building competitiveness (Cooper et al., 1997). Second, advances in large-scale and super-large-scale integrated circuits accelerated the informatization of business operations. This shift was most notably marked by the advent of Material Requirements Planning (MRP) Ⅱ, an expanded version of the original MRP system, designed to address the challenges of production planning, inventory management, and materials requirements. MRP Ⅱ integrated information across departments within a single system, which greatly enhanced both production efficiency and materials management. In 1982, Oliver and Webber (1982) formally introduced the concept of the supply chain. They described it as an operational process that covers planning, execution, and control, with its primary objective of maximizing customer satisfaction. At this stage, the supply chain began to exhibit both systemic and information-driven characteristics. On the organizational side, the focus shifted to collaboration and communication among multifunctional departments, with an emphasis on aligning plans across functions. At the same time, the deployment of MRP Ⅱ systems facilitated collaborative operations and management. Consequently, this period has come to be known as the era of Supply Chain 1.0.

Entering the 1990s, the accelerating pace of global economic integration and advancements in information technology began to reshape the perspective of supply chain management. The focus gradually shifted from optimizing internal functions and processes within organizations to achieving extensive cross-boundary coordination and integrated management, marking the advent of Supply Chain 2.0. This shift emphasized end-to-end integration across the supply chain and the use of coordination and information sharing to enhance efficiency. A key driver of this expansion was the growing recognition that organizational performance was no longer determined solely by internal process management, but rather by the performance of the entire supply chain system encompassing both upstream and downstream partners (Christopher, 2019). In this system, enterprises were increasingly required to collaborate closely with suppliers, manufacturers, distributors, and customers to create synergy and improve collective performance. At the same time, information systems, most notably Enterprise Resource Planning (ERP), were broadly adopted in business management. Building on the foundation of MRP Ⅱ, ERP systems introduced a broader set of functional modules, including finance, human resources, procurement, sales, and inventory, and integrated them within a unified platform. The introduction of ERP marked a new phase in corporate resource management, which enabled more comprehensive and precise coordination across functions. During this stage, the supply chain came to encompass all the fundamental components of supply chain management. First, in terms of organizational structure, the scope expanded beyond intra-organizational collaboration to include a network of upstream and downstream enterprises and certain strategic partners. Second, in process management, attention extended beyond physical logistics from production to sales to encompass business flow, logistics flow, information flow, and capital flow within an integrated system. Finally, regarding managerial components, supply chains were shaped by a mix of material, technological, and behavioral factors that required effective organization and management. In short, this stage marked a transition to a more multidimensional and systematized supply chain management model that had far-reaching implications for corporate operations and development (Lambert & Cooper, 2000).

Since the mid-1990s, intensified global market competition and increasingly diverse and personalized customer needs had prompted supply chain management to place emphasis on both leanness and agility (Oliveira-Dias et al., 2022). This shift marked the emergence of Supply Chain 3.0, characterized by the pursuit of both cost optimization and rapid responsiveness. Leanness became a central trend in supply chain management, aimed at minimizing operational costs through the optimization of each supply chain link. By reducing inventory, transportation, and procurement costs, enterprises could enhance overall economic efficiency. To achieve leanness, enterprises must strengthen coordination and information sharing across the supply chain to enable end-to-end integration, thereby improving visibility into market demand and supply conditions and facilitating more efficient resource allocation. In addition, agility also emerged as a critical management trend. In rapidly changing market environments, enterprises must be able to respond swiftly to shifting demand. The goal of agility was to enhance the supply chain’s flexibility and adaptability so that production and sourcing strategies could be quickly adjusted to meet customer needs. To this end, enterprises must improve the visibility, responsiveness, and adaptability of their supply chains to enable real-time coordination and collaborative operations across all segments. Whether an enterprise adopted a lean or agile supply chain depends on whether its business or product was functional or innovative. For products with stable demand, long life cycles, and low margins, a lean supply chain was more appropriate. In contrast, for products with volatile demand, short life cycles, and high margins, an agile supply chain was better suited. This alignment reflects the logic of Fisher’s (1997) well-known framework. However, whether pursuing leanness or agility, enterprises must continuously enhance collaboration and information sharing with upstream and downstream partners, develop close business relationships, and employ advanced data analytics to understand and anticipate customer needs, thereby achieving higher levels of customer satisfaction.

With the arrival of the 21st century, the operating environment of supply chains underwent a fundamental transformation. Networked structures and complex systems became the dominant organizational form, ushering in the era of Supply Chain 4.0. Hearnshaw and

Wilson (2013) summarized this networked supply chain by highlighting three key features: (1) Supply chains are increasingly organized as decentralized, web-like networks, characterized by short-chain connections between nodes; (2) the growing global scope of supply chains demands heightened attention to incentive alignment, coordination, and integration; and (3) supply chain management in this stage is grounded in multi-party relationships and the management of both information and social capital. Other scholars described supply chains at this stage as complex adaptive systems composed of interconnected nodes and links (Carter et al., 2015). Meanwhile, modern digital technologies, commonly called ABCD (AI, blockchain, cloud computing, and big data), opened the door to the Fourth Industrial Revolution. These technologies provided the foundation for digitalizing supply chains and accelerating their evolution toward greater intelligence and platformization. In this stage, supply chain operations increasingly focused on integrating lean and agile principles, giving rise to the concept of the leagile supply chain (Naylor et al., 1999), a digitally enabled configuration that used advanced technologies to optimize and automate each link in the supply chain and ultimately enhanced efficiency, transparency, and flexibility.

Supply Chain 5.0, the stage defined by an AI-based supply chain, has emerged as a highly anticipated new direction in recent years. AI has emerged as a critical driving force behind the development of supply chains, primarily due to two factors. First, growing global uncertainty and the rise of deglobalization have intensified concerns over the security and resilience of supply chains. As a result, enterprises and industries are increasingly focused on how to leverage human-machine interaction to enhance proactive responsiveness and adaptability to external uncertainties (Shi et al., 2025). Second, the transition from Industry 4.0 to Industry 5.0 has accelerated the digital transformation of supply chains. Industry 4.0 integrates technologies such as the IoT, cloud computing, cyber-physical systems, and cognitive computing to enable the creation of smart factories, where real-time monitoring and data analytics support fast and efficient decision-making. By contrast, Industry 5.0 aims to reintroduce human participation into industrial production and emphasizes collaboration between humans and intelligent systems. It seeks to enhance human decision-making through cognitive computing and AI, while addressing societal and sustainability challenges such as inclusive workforce development, waste reduction, and promoting circular economy models (Leng et al., 2022; Xu et al., 2021). These forces make it clear that effective supply chain operations and management must balance leanness and agility while incorporating advanced intelligence. Intelligent supply chains enable human-machine collaboration, deepen insight into the roles and functions of all stakeholders, and allow actors to better understand material sources, product demands, and their interdependencies. This, in turn, aids in the prevention of disruptions and enhances the capacity to navigate ecological complexity. Moreover, intelligent decision-making empowers each party to apply its expertise, core competencies, and knowledge to support sustainable supply chain development through effective ecosystem governance.

3 AI-Based Intelligent Supply Chains and Their Core Characteristics

Both scholars and practitioners continue to explore how to define an AI-based intelligent supply chain. Some definitions emphasize the operational features of the supply chain itself; others focus on the functions AI performs within supply chain operations; still others link specific supply chain activities to matching AI techniques. For example, some researchers propose that a supply chain qualifies as AI-based and intelligent if it simultaneously meets two criteria: (1) It can make autonomous decisions to achieve supply chain management objectives, and (2) it can do so under partially unknown conditions (Baryannis et al., 2019). This definition implies that AI-based supply chains utilize autonomous contextual learning to support decision-making processes. Other scholars define AI-based intelligent supply chains by the roles AI plays in supply chain management, such as demand forecasting, inventory management, revenue management and marketing, transportation management, and risk analysis across the supply chain (Choi et al., 2018). Yet another line of research identifies four principal AI applications in supply chain operations: inventory control and planning, procurement and supply management, demand planning and forecasting, and order-fulfillment decision-making (Sharma et al., 2022). Finally, some studies examine the key AI technologies that enable these capabilities. For example, Toorajipour et al. (2021) show that the primary AI techniques used in intelligent supply chain operations include artificial neural networks for uncovering complex patterns beyond human detection, fuzzy logic and models to handle partial truths and multivalued reasoning, and multi-agent or agent-based systems that perceive their environment and autonomously solve specific problems.

Although the definitions and interpretations reviewed above highlight certain aspects of AI-based intelligent supply chain operations, they fall short of capturing AI's unique, overarching role in supply chain operations, particularly how AI improves performance (Helo & Hao, 2022). To fill this gap, we define an AI-based intelligent supply chain as:

A comprehensive, integrated system of technology and management underpinned by AI and machine learning, engineered to deliver intelligent, networked, coordinated, integrated, and automated operations. Through human-machine collaboration and integration, such a supply chain evolves into an autonomous system that is capable of self-awareness, self-determination, and self-optimization, with resilience and sustainability as its core development objectives.

This definition may be understood in terms of the foundation, approach, methods, and outcomes of supply chain operations and management.

From a foundational perspective, an AI-based intelligent supply chain depends on AI and machine learning to automate decision-making and deliver higher efficiency, fewer errors, and deeper insights. As data volumes grow and algorithms advance, AI applications in supply chains have become increasingly widespread. First, AI-based supply chains can improve efficiency by automating decision-making processes. In traditional supply chain management, such processes typically rely on human intervention, resulting in inefficiencies and a higher risk of errors. In contrast, AI and machine learning technologies allow enterprises to automate these decision-making processes, thereby increasing speed and enhancing accuracy. For example, a machine learning model that analyzes historical sales data can automatically determine optimal inventory levels and prevent both overstocking and stockouts. Second, AI-driven supply chains can reduce errors. In traditional supply chain management, human factors are among the primary sources of errors. With AI and machine learning, enterprises can minimize manual intervention and lower error rates. For example, natural language processing can automatically process order data and help eliminate human-caused errors. Finally, AI-based supply chains can generate deeper insights. AI and machine learning technologies enable real-time analysis and prediction based on large volumes of data and allow enterprises to better understand market dynamics and customer needs. For example, big data analytics applied to customer purchasing behavior can reveal future sales trends and support more effective inventory and logistics planning.

With respect to the approach to supply chain management, the AI-based intelligent supply chain functions as an integrated technology and management system that combines AI, the IoT, big data, and other advanced technologies. Its core objective is to achieve intelligence, networking, coordination, integration, and automation. This advanced approach offers enterprises new perspectives and methods to address increasingly complex market environments and constantly evolving customer needs. By applying techniques such as machine learning and deep learning, the AI-based intelligent supply chain enables data analysis and forecasting to support intelligent decision-making. Through the automatic identification of patterns and trends, AI helps enterprises respond swiftly to market shifts, enhance operational efficiency, and reduce risks. IoT technologies connect various nodes within the supply chain to form a tightly coordinated network. This not only improves the speed and accuracy of information transmission but also allows supply chain actors to share data and resources in real time, thus enabling joint responses to challenges. Moreover, the AI-based intelligent supply chain integrates data and processes across different segments of the supply chain, thus forming a cohesive system. This integrated management approach allows enterprises to gain a comprehensive understanding of overall supply chain operations and to identify potential issues early. In addition, it enables a high degree of automation across numerous tasks, such as order processing, inventory control, and logistics scheduling. Automation not only reduces human error and improves efficiency but also frees up employees' time and energy to focus on higher-value activities.

As for the methods of supply chain management, the core of the AI-based intelligent supply chain lies in human-machine collaboration and integration. Through AI technologies, people can access more data and information to better understand the real-time status and evolving trends across all segments of the supply chain. At the same time, AI provides decision-making support that helps improve the accuracy and scientific basis of managerial choices. By learning from and analyzing human experience and decision-making, AI continuously refines its algorithms and models to offer more intelligent and efficient supply chain management. As such, the AI-based intelligent supply chain can be viewed as an autonomous system characterized by self-awareness, self-determination, and self-optimization. It not only enables intelligent and automated supply chain management through human-machine collaboration and integration but also improves its own capabilities and efficiency through ongoing learning and optimization. This provides enterprises with more reliable and efficient supply chain management solutions and strengthens their competitive advantage.

In terms of the outcomes of supply chain management, the application of advanced technologies such as AI and big data allows the AI-based intelligent supply chain to improve efficiency, reduce costs, and continuously monitor and analyze each segment of the supply chain in real time. This enables the timely identification of potential issues and risks, as well as the provision of effective solutions. Such capabilities enhance the supply chain's resilience and adaptability when facing disruptions. Moreover, by optimizing resource allocation, reducing waste, and improving energy efficiency, the AI-based intelligent supply chain helps enterprises pursue more environmentally friendly and energy-efficient operations. AI also enables enterprises to better understand and meet customer needs, leading to the development of more competitive green products and services and supporting the transition of industries toward greater sustainability.

Given the characteristics outlined above, the AI-based intelligent supply chain shares certain similarities with the digital supply chain, such as the use of advanced digital technologies, but the two differ in many important ways. These differences span their technological foundations, core features, data utilization, degree of automation, predictive capabilities, adaptability, security, and cost-effectiveness (see Table 1).

Table 1 Differences between AI-Based Intelligent Supply Chains and Digital Supply Chains

Item	AI-based intelligent supply chain	Digital supply chain
Technological foundation	Advanced technologies such as AI, big data, cloud computing, and the IoT	Mature technologies such as the internet, big data, cloud computing, and the IoT
Core features	Using AI technologies for data analysis and prediction to enable intelligent decision-making and optimization	Using digital technologies to drive digital transformation and automation of the supply chain
Data application	Applying AI to deeply mine and analyze large volumes of data to enable intelligent decision-making in the supply chain	Applying big data technologies to store, process, and analyze data for supply chain optimization
Degree of automation	Highly automated, with AI technologies enabling fully automated supply chain operations	Moderately automated, with information technologies supporting partial automation of supply chain tasks

(*To be continued*)

(*Continued*)

Item	AI-based intelligent supply chain	Digital supply chain
Predictive capability	Strong predictive capability through AI-driven forecasting and optimization of the supply chain	Limited predictive capability based on traditional data analysis techniques for forecasting and planning
Adaptability	High adaptability to rapidly respond to market changes and resolve supply chain issues	Limited adaptability, requiring human intervention to respond to changes and solve supply chain issues
Security	Strong security, using AI for real-time monitoring and risk prevention across the supply chain	Moderate security, using information technologies for managing and protecting supply chain security
Cost-effectiveness	Highly cost-effective, with AI enhancing efficiency, reducing costs, and improving resilience and sustainability	Moderately cost-effective, using digital technologies for cost control and operational optimization

4 Operating AI-Based Intelligent Supply Chains from the Supply and Demand Perspectives

Whether AI-based intelligent supply chains can truly realize their intended features, deliver corresponding benefits, and ultimately promote the supply chain's development toward greater efficiency, resilience, and sustainability does not depend solely on advancements in AI technologies themselves (Jöhnk et al., 2021). In fact, to fully understand this transformation, it is essential to analyze the conditions and fundamental prerequisites for AI-based intelligent supply chain operations from both the supply and demand perspectives (see Figure 2).

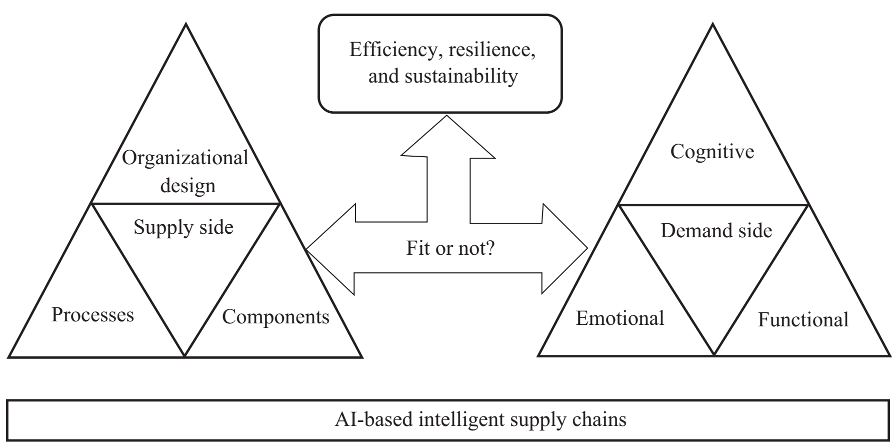

Figure 2 AI-Based Intelligent Supply Chains from the Supply and Demand Perspectives

From the supply perspective, the effective functioning of an AI-based intelligent supply chain depends on the presence of well-structured organizational systems, integrated processes, and coordinated elements. Without these foundations, even the most advanced AI technologies and promising applications cannot be effectively integrated into supply chain operations, let alone achieve the goals of efficiency, resilience, and sustainability. Therefore, in advancing AI-based intelligent supply chains, it is necessary to prioritize the development of robust organizational structures, process integration, and element coordination to create favorable conditions for applying AI in supply chain management. From the demand perspective, it is crucial to consider how beneficiaries or customers perceive the value of AI-based intelligent supply chains. In other words, the value of AI in the supply chain is not determined solely by the capabilities or solutions provided by the supply side; it is also closely linked to the customer's understanding and behavioral responses. Only when customers truly recognize and accept the benefits brought by AI can the development of AI-based intelligent supply chains be effectively promoted.

On the supply side, the construction and development of any supply chain relies on three key elements: structure, processes, and components, collectively referred to as the Structure-Process-Components (SPC) model in supply chain analysis (Lambert & Cooper, 2000). Therefore, to advance an AI-based intelligent supply chain, enterprises must address challenges in organizational design, processes, and components.

Regarding the organizational structure of the supply chain, two main challenges must be addressed to promote AI-based intelligent supply chains. It is essential to build a digital ecosystem, a business ecosystem, and an environmental ecosystem. The digital ecosystem involves the symbiosis of various digital technologies and services, including the IoT, big data analytics, and cloud computing. These technologies and services must be coordinated and integrated to enable the digitalization and intelligence of the supply chain. The business ecosystem concerns the coordination and integration of various economic actors, such as suppliers, manufacturers, and distributors, who must collaborate, share information and resources, and jointly promote efficient supply chain operations. The environmental ecosystem relates to the alignment of environmental, social, and governance (ESG) factors. Enterprises must consider environmental protection, social responsibility, and sound governance when managing supply chains to achieve sustainable development. Moreover, it is equally critical to maintain balance and achieve integration among the three ecosystems. The digital, business, and environmental ecosystems influence and constrain one another, and a major challenge is how to reconcile their different interests and needs. For example, digitalization and intelligent supply chains may lead to increased energy consumption and carbon emissions, which potentially conflict with environmental objectives, thus requiring trade-offs and adjustments. Similarly, tensions may arise between business and environmental goals: For instance, to reduce costs and improve efficiency, supply chains might favor suppliers that rely on cheap labor or have low environmental standards, which clashes with principles of environmental and social responsibility. To address these tensions, enterprises must adopt strategies that promote convergence and alignment across all ecosystems.

With regard to supply chain processes, both human and machine agents must overcome a range of obstacles and challenges across the four key phases of collaboration: reaching a willingness to cooperate, establishing collaboration, maintaining collaboration, and developing collaboration. In the phase of reaching a willingness to cooperate, a critical issue is resolving the tension between interdependence and conflict of interests among collaborating enterprises. The interconnection and coordination between supply chain organizations are fundamental to enabling AI systems to process business data intelligently. Moreover, AI systems must collect information from multiple heterogeneous data sources and then synchronize and integrate this information for analysis and processing. This entails handling data in differing formats and structures, making it necessary to resolve inconsistencies and conflicts to ensure data accuracy and completeness. In the phase of establishing collaboration, challenges arise in aligning business processes among enterprises and ensuring the connectivity and standardization of technical infrastructures, both of which affect AI's capacity for autonomous learning. The former makes it difficult to integrate the operations and data of different enterprises into a unified AI system, while the latter creates barriers to interaction and interoperability between humans and machines. In the phase of maintaining collaboration, the extension and increasing complexity of corporate operational resources, along with the need for system enhancement and iteration, pose further challenges to AI's ability to adapt autonomously. Finally, in the phase of developing collaboration, it becomes essential to address the coordination of diverse corporate value orientations and the autonomous execution and insight capabilities of technological systems.

When it comes to the components of supply chains, AI is reshaping the elements and capabilities of supply chain management, with algorithms and technologies gradually replacing traditional management tools and methods. This shift raises several new issues that must be addressed. First, although AI algorithms can reflect the state of supply chain operations more intelligently and accurately, it remains an open question whether algorithmic trust, particularly within supply chains, can fully replace human factors. As digital technologies continue to evolve, some studies argue that new technologies have achieved algorithmic trust (Chawla, 2020), thereby resolving challenges stemming from interpersonal trust in traditional supply chains. However, this view is debatable. Algorithmic capability is not determined by a single technology but typically relies on the integration of various digital technologies, such as the combination of AI and blockchain. Moreover, while algorithms may temporarily inspire confidence among actors, they are unlikely to fully substitute for human input in building long-term trust and management capabilities. This raises a new challenge: how to effectively integrate machines and algorithms, and algorithms with human actors, in order to establish a new form of management competence and trust. Second, as AI continues to advance, its technical capabilities, particularly in security, have become critical to the development of supply chains. Enterprises applying AI technologies must take robust data protection measures such as encryption and access control to prevent the leakage of sensitive information. At the same time, they must conduct security assessments and testing of AI systems to detect and resolve potential vulnerabilities. Moreover, enterprises should establish comprehensive security management frameworks, including staff training on security awareness and the implementation of security audit mechanisms, to enhance the overall safety and resilience of the supply chain.

From the demand perspective, the role of AI in the supply chain depends on users' cognitive, emotional, and functional recognition.

In terms of cognitive recognition, whether AI can be effectively integrated into supply chain operations hinges on the level of acceptance among supply chain actors, namely, whether economic actors within the supply chain recognize AI's potential to enhance or improve efficiency. In fact, it is not the algorithm itself but the user's perception that generates a sense of acceptance or recognition (Shin et al., 2020). This cognitive perception is primarily reflected in the FAT framework: fairness, accountability, and transparency. Fairness is a complex and often debated concept, but it is generally agreed that fair AI algorithms produce decisions free from bias, discrimination, or unjust outcomes (Diakopoulos, 2016). In other words, AI should generate results in an impartial manner, unaffected by human subjectivity or prejudice. Therefore, the perception of fairness is not merely tied to the accuracy (i.e., the correctness of results) or precision (i.e., the consistency of results) of AI, but more importantly, to the perceived justice and objectivity brought about by the algorithm. Accountability refers to the responsibility for the outcomes of AI-driven decision-making, specifically, the ability to trace and attribute errors resulting from the inappropriate use of AI to a responsible party or decision-maker. Transparency demands that the processes and outcomes generated by algorithms be open and comprehensible to users (Shin & Park, 2019). However, due to the proprietary nature of data and the complexity or opacity of algorithms, users often struggle to understand the mechanics behind AI systems or how their results are produced. This opacity can lead to distrust or skepticism of AI's role and outcomes. Hence, transparency is critical to whether AI will be accepted and trusted in supply chain management.

When it comes to emotional recognition, it refers to users' sense of closeness to AI and their perceived psychological distance from it. The effectiveness of AI in supply chain operations is influenced not only by cognitive factors but also by emotional ones, that is, the degree to which humans are psychologically comfortable with its use. This emotional dimension includes tangibility, task characteristics, and responsiveness of AI systems (Glikson & Woolley, 2020). Tangibility refers to how the physical presence or form of AI affects emotional acceptance. For instance, one study finds that people are more likely to accept suggestions from a three-dimensional robot than from a computer, clearly showing that the tangible form of AI can influence emotional receptiveness (Shinozawa et al., 2005). Task characteristics indicate that people are more emotionally inclined to accept the involvement of AI in specific task-related decision-making. Other research has shown that humans tend to trust AI more when it comes to functional decision-making, whereas they are less receptive when decision-making involves human-centered or moral considerations (Glikson & Woolley, 2020). Responsiveness refers to the AI's ability to engage in adaptive and timely interaction with humans. Enhanced AI systems like ChatGPT demonstrate high levels of responsiveness and provide interactive feedback in real time based on users' needs and input.

Finally, functional recognition refers to users' expectations regarding the capabilities of AI algorithms, specifically, whether these algorithms can provide the level of support needed for decision-making in supply chain operations. In the field of information management, the Technology Acceptance Model (TAM) emphasizes two key factors that influence user adoption: perceived usefulness and ease of use (Davis, 1989). This model also applies to AI-based intelligent supply chains. In addition, reliability is a crucial factor. If AI systems consistently make errors, users will inevitably lose confidence in them (Glikson & Woolley, 2020).

5 Governance of AI-Based Intelligent Supply Chains

The deep integration of AI with supply chains brings about another critical issue, namely, governance. Supply chain governance refers to a management model that oversees and coordinates the activities, decisions, and relationships among various supply chain actors, including suppliers, manufacturers, distributors, retailers, and logistics service providers (Hua et al., 2021). The goal of supply chain governance is to improve efficiency, flexibility, responsiveness, and customer satisfaction through effective decision-making and execution, while also reducing risks and costs. Ultimately, it aims to enable shared value creation and sustained success for all stakeholders involved.

In supply chain governance, traditional approaches primarily include contractual governance and relational governance. Contractual governance refers to a formal mechanism grounded in legal frameworks, wherein supply chain actors define their responsibilities, rights, and obligations through detailed contracts or agreements (Song & Liu, 2012). These contracts serve as both the legal basis for collaboration and essential tools for dispute resolution. The decision-making process in contractual governance relies on the legal system, and enforcement is typically carried out through third-party safeguard mechanisms such as court rulings and arbitration decisions. This form of governance is characterized by the following natures. The first is mandatory. Contracts are legally binding, and all parties must comply with the agreed forms; otherwise, they will face legal sanctions. This mandatory nature ensures the effective enforcement of contracts. The second is its protective nature, as third-party safeguard mechanisms such as courts and arbitration ensure a fair and just environment for resolving disputes and protecting the rights and interests of all parties are not violated. And the third is its regulatory nature, which emphasizes clarity and specificity in regulating expected behaviors and outcomes, thereby reducing uncertainty and improving cooperation efficiency. In contrast, relational governance emphasizes the development and maintenance of long-term, trust-based cooperative relationships among supply chain actors.

Rather than relying solely on legal contracts, it promotes collaboration through information sharing, coordinated decision-making, joint problem-solving, and the creation of relationship-specific assets. Decision-making under relational governance is based on shared social norms and mutual expectations about the future, with enforcement rooted in trust and common understandings. When behavior violates collective interests, informal mechanisms such as group sanctions may be employed (Das & Teng, 2002). Compared to the formal, legalistic nature of contractual governance, relational governance is inherently informal, socially embedded, and network-oriented.

Unlike the two traditional approaches mentioned above, the widespread adoption and advancement of modern digital technologies, particularly the ongoing integration of AI into industrial operations, has given rise to a new governance model known as algorithmic governance (Danaher et al., 2017). Algorithmic governance refers to a mode of governance that relies on algorithms, AI, and big data technologies to support decision-making, enforce rules, and manage systems (Issar & Aneesh, 2022). In this model, complex computational programs and data analytics are employed to address various social, economic, and political challenges with the aim of improving efficiency, reducing bias, and enhancing transparency. Decisions are driven by data and algorithmic analysis, which represent the outcomes of algorithmic models that process and interpret large volumes of data. Execution is carried out through automated processes and machine learning systems that monitor, adjust, and implement decisions in real time, often supplemented by human oversight and intervention.

However, whether algorithmic governance can exist independently within supply chain operations remains open to debate. This is because supply chain operations typically involve communication, coordination, and collaborative actions among different economic actors, often encompassing complex interpersonal or task-based relationships. Although AI can enhance the efficiency of supply chain decision-making and promote greater intelligence in operations, human actors continue to play a critical role as the core agents of supply chain operations and management. Actor-Network Theory (ANT) offers a distinctive perspective for analyzing social phenomena and technological practices by emphasizing the importance of interactions among actors and the process of constructing networks, including the role of non-human elements in shaping social structures. According to this theory, both humans and technologies act as influential agents, and the relationships among them are dynamic and continuously evolving, formed through ongoing negotiation and translation processes (Hald & Spring, 2023).

Therefore, the governance of AI-based intelligent supply chains adopts a hybrid model that integrates contractual governance, relational governance, and algorithmic governance. This mixed governance approach draws on legal frameworks and social norms as well as computational power and digital technologies to inform decision-making. Its implementation relies on a balanced integration of the execution mechanisms associated with each of these governance types.

The operation of a hybrid governance model in AI-based intelligent supply chains is often shaped by the complexity of tasks and the diversity of actors involved (see Figure 3).

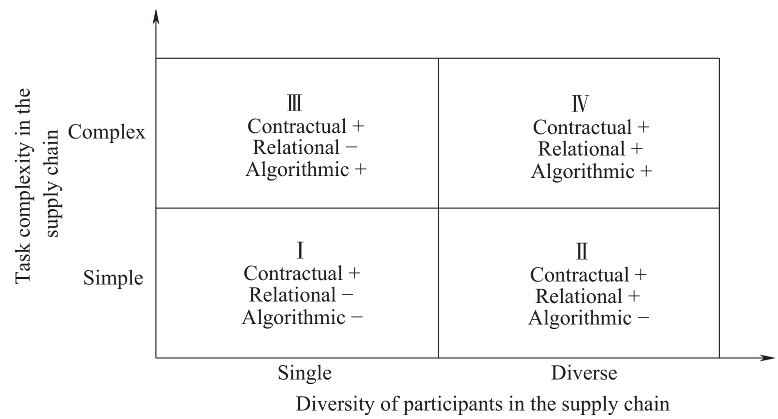

Figure 3 Hybrid Governance Mechanism of AI-Based Intelligent Supply Chains
Note. "+" indicates a dominant factor, while "–" indicates a supporting factor.

In Paradigm Ⅰ, the supply chain involves relatively few actors, or the operations and decision-making are centered around a specific enterprise, with low task complexity. In such scenarios, contractual governance is the dominant model, providing straightforward and well-defined responsibilities and obligations. Relational and algorithmic governance only play auxiliary roles. In Paradigm Ⅱ, although the tasks are relatively simple, the supply chain includes a large number of diverse participants, requiring communication and coordination among various actors. Therefore, alongside contractual governance, relational governance has become a key determinant of operational efficiency, while algorithmic governance remains secondary. This is because when tasks are easier to identify and evaluate, the role of digital technologies and AI is limited. In Paradigm Ⅲ, although the supply chain involves fewer entities, the complexity of tasks increases significantly. Relying solely on contractual governance struggles to address challenges such as generating insightful problem identification and enabling real-time, precise decision-making. Consequently, the role of AI algorithms will be greatly amplified.

Paradigm Ⅳ represents a typical complex adaptive system in supply chain management, characterized by both a high number and diversity of participants and high task complexity. Algorithmic governance becomes particularly important, as it enables actors to gain deeper insights into supply chain dynamics, optimize decisions in real time, and adjust cooperation strategies based on evolving contexts and relationships. This approach provides high flexibility and efficient resource allocation. However, the roles of contractual and relational governance should not be overlooked in this paradigm. They complement algorithmic governance to form an effective governance system. Specifically, contractual governance offers the necessary legal frameworks and rule-based foundations within complex adaptive systems. While algorithms can process vast amounts of data and generate decision recommendations, final decisions and actions must still operate within the constraints of laws and agreements. Clearly defined contractual terms establish the rights and obligations of all parties, provide a basis for resolving disputes, and help delineate the boundaries and standards for algorithmic operations, thus preventing misuse or abuse. Relational governance plays a crucial role in networks with diverse and complex participants. In supply chains, trust, communication, and collaboration are essential for maintaining their stability and efficiency. Relational governance helps establish and sustain long-term, trust-based partnerships. It facilitates information sharing, coordinated decision-making, and joint problem-solving. Furthermore, it mitigates the coldness and mechanical nature often associated with algorithms by preserving human-centered interaction and empathy. Moreover, both contractual and relational governance can compensate for some of the limitations of algorithmic governance. For instance, algorithms may be unable to fully capture contextual nuances and interpersonal dynamics, which can significantly impact real-world operations. In sum, in supply chains with Paradigm Ⅳ, algorithmic, contractual, and relational governance complement one another to form a governance system capable of addressing complexity and uncertainty while ensuring fairness, transparency, and sustainability.

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