Journal of Business Logistics

WILEY

ORIGINAL ARTICLE

Robot Built Different: How It Affects Supply Chain Resilience

Yu Yu[1] | Zhaoyue Li[2] | Sachin Kumar Mangla[3,4] | Malin Song[5]

[1]School of Business, Nanjing Audit University, Nanjing, China | [2]School of Management, Xiamen University, Xiamen, China | [3]Jindal Global Business School, O P Jindal Global University, Sonipat, India | [4]Plymouth Business School, University of Plymouth, Plymouth, UK | [5]Collaborative Innovation Center for Ecological Economics and Management, Anhui University of Finance and Economics, Bengbu, China

Correspondence: Malin Song (songmartin@163.com; songml@aufe.edu.cn)

Received: 28 October 2024 | **Revised:** 17 May 2025 | **Accepted:** 12 June 2025

Funding: This work was supported by National Natural Science Foundation of China (72171122, 71934001, 72171124).

Keywords: digital transformation | dynamic capability theory | innovation strategy | robot adoption | spillover effects | supply chain resilience

ABSTRACT

Technological evolution has driven the widespread adoption of industrial robots while increasing the resilience requirements of increasingly complex supply chains. However, the relationship between robot adoption and supply chain resilience remains underexplored. This study addresses this gap by empirically examining the impact of robot adoption on supply chain resilience, using a panel dataset of listed manufacturing firms in China from 2013 to 2022. The findings reveal that robot adoption not only significantly enhances a firm's own supply chain resilience but also exerts a positive spillover effect on the resilience of its upstream and downstream partners. Moreover, the study uncovers the moderating roles of enterprise innovation and digital strategies, which amplify the positive effects of robot adoption on supply chain resilience. By integrating technological, strategic, and network perspectives, this research offers novel empirical evidence on the interplay between automation and resilience in supply chains. The study's conclusions have important implications for both managerial practice and policymaking: while state-owned and high-tech enterprises should be encouraged to take the lead in robot adoption, firms more broadly can further enhance supply chain resilience by investing in innovation and digital transformation strategies.

1 | Introduction

Economic globalization is currently facing considerable challenges, with an increase in trade protectionism and substantial shifts in the global governance system (Guedhami et al. 2022). The increasing uncertainty and unpredictability in the global environment have led to frequent disruptions in logistics, shortages of raw materials, production halts, and interruptions in the supply of goods. These factors significantly impair the flow of resources and make supply chain risk management more challenging (Mateska et al. 2024). For example, in 2022, the COVID-19 outbreak in parts of China forced major automobile manufacturers, such as NIO and Tesla, to halt production because they had insufficient parts, resulting in severe supply chain disruptions. This situation highlights the critical need for robust supply chain resilience among enterprises to mitigate risk (Zsidisin and Wagner 2010). The supply chain integration and the complexity of the supply chain put forward higher requirements for the resilience of the supply chain.

In parallel, the swift advancement and broad implementation of automation technologies, particularly industrial robots, have emerged as crucial drivers of productivity and supply chain efficiency (Antonioli et al. 2024; Cilekoglu et al. 2024). Many enterprises have already integrated industrial robots into their supply chain management processes (Maghazei et al. 2022). Industrial robots have penetrated the manufacturing industry and even affected the development of the industry, becoming a new hot topic in the field of supply chain management. For example, companies in industries such as automotive or electronics use robots to complete tasks such as assembly, inspection, and quality control, helping to reduce production costs while increasing output and enhancing the flexibility of the manufacturing process to cope with interruptions. Automated mobile robots and robotic arms are deployed in the warehouse for inventory management and order sorting. Besides, robots are used in e-commerce logistics order fulfillment systems for tasks such as sorting packages, sorting orders, and last-mile delivery.

This phenomenon raises the following important questions: Can the adoption of advanced technologies, particularly robots, stabilize and optimize supply chains in turbulent environments? How does this process unfold? Addressing these questions provides a theoretical foundation for companies seeking to increase their supply chain resilience. Previous research has focused on the role of industrial robots in various parts of the supply chain. In particular, new technology, such as robotics, plays an important role in enhancing supply chain agility and supply chain collaboration (George et al. 2022; Srinivasan and Swink 2018). However, theoretical and empirical studies on robot adoption in ensuring supply chain resilience remain scarce. Liu et al. (2016) explore the impact of new technologies and capacity allocation on supply chains from the perspective of resource orchestration. Industrial robots have an important effect on supply chain robustness. Our study further extends the research on the development of supply chain resilience from the perspective of industrial robot adoption by providing new evidence and theoretical perspectives.

With the widespread deployment of industrial robots in the manufacturing industry, more and more studies have begun to focus on their role in enhancing firms' operational efficiency, flexible production, and risk response capabilities (Grover and Ashraf 2024; Koreis et al. 2025; Rainer Jr et al. 2025). However, the literature has mostly focused on its direct impact on firm performance or manufacturing capability, ignoring the important moderating effect that firm strategic characteristics may have on this relationship. In fact, in the process of introducing advanced manufacturing technologies such as industrial robots, a firm's own strategic orientation and development path often affect the effectiveness of technology adoption (Wei et al. 2022). In particular, digital transformation strategy and innovation strategy, as important directions for firms to cope with environmental uncertainty and seek long-term competitive advantage, may, to varying degrees, strengthen or weaken the actual enhancement of supply chain resilience by technological inputs. In other words, even if firms adopt similar technological tools, their improvement effects on resilience may differ depending on strategic differences (Negri 2025; Xu et al. 2024). Therefore, identifying and examining the moderating effects of these strategic variables can help clarify the boundary conditions of the Technology-Resilience relationship and provide theoretical support for firms to formulate differentiated strategies.

On this basis, does the adoption of industrial robots generate spillover effects in the supply chain network? That is to say, is it possible that the technological upgrading behavior of an enterprise may indirectly affect the latter's supply chain resilience performance through the upstream and downstream enterprises with which it has cooperative, trading, or synergistic relationships? In a highly coupled modern supply chain, information, logistics, and value flows among enterprises are intertwined, and technological changes in one party often drive process adjustments and capacity building in related enterprises (Kumar and Raj 2025). For example, a core enterprise's digital manufacturing model may force suppliers to upgrade their systems or motivate downstream customers to optimize their operational resilience (Zhang, Liang, and Chen 2025). In this process, firms' technology adoption behaviors may be transmitted across firms through collaborative mechanisms, knowledge sharing, or strategic imitation, thus systematically affecting the resilience of the entire supply chain system. However, research on this supply chain resilience spillover effect is still very limited, and the related mechanisms have not been fully revealed, and there is a lack of systematic empirical evidence. The existence of spillovers not only expands the boundaries of technological value but also provides a theoretical basis for the evaluation of corporate return on investment and policymaking with a more external perspective.

To address the identified research gap, this study empirically examines the impact of industrial robot adoption on the supply chain resilience of Chinese manufacturing enterprises using microlevel data from domestically listed firms between 2013 and 2022. A fixed effects regression model is employed to estimate the core relationship, followed by a heterogeneity analysis to identify variations across different firms. The study further explores the moderating roles of firms' digital transformation and innovation strategies, using the Johnson–Neyman method to test the conditional effects. In addition, by integrating supply chain network structure data, the analysis investigates whether and how robot adoption by focal firms influences the resilience of upstream and downstream partners, thereby identifying potential spillover effects within the supply chain network. Together, these analyses offer deeper insights into the mechanisms through which industrial robot adoption shapes supply chain resilience and provide evidence-based implications for managerial practice and policy formulation.

Compared with previous qualitative or descriptive research, this study offers new micro insights into the practical adoption of robots and mechanisms for enhancing supply chain resilience on the basis of an empirical analysis of relevant data. This study provides new evidence for robot adoption in the manufacturing industry to promote the development of supply chain resilience. The theoretical insights of this study are essential for boosting confidence in robot adoption and advancing the development of supply chain resilience. In addition, the innovation of this paper is that it further explores the spillover effect in the supply chain. Observing the robot adoption of enterprises can also improve the supply chain resilience of suppliers and customers. Through heterogeneity analysis and moderating effect analysis, more detailed guidance for the development of enterprises and policymaking can be provided. On the one hand, policymaking should strengthen the leading role of state-owned enterprises and high-tech enterprises. On the other hand, enterprises can deepen the role of robot adoption in improving supply chain resilience by increasing attention to innovation and digital transformation strategies. This study complements the existing research, represents an advancement in the field, and contains originality.

The rest of the paper is organized as follows: Section 2 presents related studies and research hypotheses. Section 3 defines key variables and describes the model and data sources. Section 4 derives the results of the empirical analyses. The findings of the mechanism and heterogeneity studies are also presented in Section 4. Section 5 investigates spillover effects in the supply chain. Conclusions and policy suggestions are provided in Section 6.

2 | Literature Review and Research Hypotheses

2.1 | Robot Adoption

The growing adoption of robots has sparked debates over their economic viability. Many studies have concentrated on how robots affect the labor market and the structure of the workforce, although mixed results have been obtained. Some research indicates that robot adoption negatively affects low-skilled workers (Kude et al. 2023), whereas others argue that it improves wage conditions and creates new job opportunities (Dixon et al. 2021). While robots may reduce the number of jobs in manufacturing, growth in business services often compensates for this loss. Moreover, robot adoption significantly boosts total factor productivity, with more intensive robot use correlating positively with higher productivity (Armstrong and Shah 2023). Robot adoption also increases a firm's likelihood of exporting, leading to larger export volumes and contributing to international trade growth (Cilekoglu et al. 2024).

Some studies suggest that the economic effects of robot adoption stem from its role in promoting firms' innovation and digital transformation strategies (Armstrong and Shah 2023). In terms of sustainability, robots contribute to energy efficiency, lower carbon emissions, and enhanced green efficiency, thus optimizing development structures (Tóth et al. 2022).

Previous studies have explored the role of industrial robot adoption in all aspects of the manufacturing industry. However, research on the advancement of industrial robots in the field of supply chains is relatively lacking. The existing research focuses on exploring the role of new technologies such as industrial robots in improving supply chain agility and supply chain collaboration (George et al. 2022; Srinivasan and Swink 2018). However, there is still a lack of theoretical and practical research on the adoption of robots in ensuring the resilience of the supply chain.

2.2 | Supply Chain Resilience

In the early stage of supply chain resilience research, resilience was usually regarded as a static concept. Early theories focused on structural aspects, such as maintaining excess capacity or buffering inventory to absorb shocks (Qi et al. 2023; Wieland and Durach 2021). This capacity allows enterprises to recover to their original state or even improve after experiencing a disruption. Resilience is measured by the supply chain's condition before and after the disruption, making it a static capability.

In the context of supply chain resilience, the dynamic capability of enterprises is crucial because it enables the supply chain to maintain flexibility and responsiveness in the face of disruptions, whether due to natural disasters, economic shocks, or geopolitical events. Therefore, this paper explores supply chain resilience from the perspective of dynamic capability theory.

Supply chain managers aim to build dynamic capabilities to respond to unexpected risks with minimal costs and losses (Todo et al. 2016; Wang et al. 2023). Dynamic capabilities refer to an enterprise's ability to continually update, reset, and adapt its resources and core competencies to adjust to changing environments, fostering continual improvement (Teece et al. 1997). Sodhi and Tang (2021) emphasized that to thrive in evolving environments and meet future societal expectations, enterprises must build self-sustaining supply chain resilience by developing dynamic capabilities. Furthermore, Müller et al. (2023) contended that dynamic capabilities are essential for effectively managing resilience within supply chains. Dynamic capability theory emphasizes active management, a long-term strategic vision, and agile decision-making, which is an important perspective for understanding and studying supply chain resilience.

The concept of supply chain resilience (Pettit et al. 2010) aligns with dynamic capabilities theory. This resilience framework states that supply chain resilience depends on the unity of vulnerability factors and capabilities (Pettit et al. 2013). The framework posits that resilience depends on balancing vulnerability and capability factors; excessive vulnerability leads to risk, whereas excessive capabilities lead to inefficiencies. Optimal resilience is achieved when these factors are balanced (Pettit et al. 2019). It is an active risk management framework that helps organizations build resilience before a crisis rather than just reacting after a crisis. This conceptual framework of resilience also encourages agile decision-making, which is critical for quickly responding to disruptions in today's fast-paced, interconnected global supply chains. This is the latest achievement of the dynamic capability theory framework in supply chain resilience management.

The traditional measurement of supply chain resilience is from a static point of view. Although Pettit et al. (2010) proposed the concept of supply chain resilience, which is consistent with dynamic capability theory, they did not clearly propose a corresponding measurement method, which is why the idea has not been popularized. This paper first proposes a measurement method for supply chain resilience based on dynamic capability theory, which extends the advanced theory of Pettit et al. (2010).

2.3 | Spillover Effects

Many studies have investigated the spillover effect of the supply chain: Bianchi and Giorcelli (2022) reported that management intervention had a positive spillover effect on the supply chain of trained companies. De Vito et al. (2025) study the spillover effect of a corporate tax increase, which has a negative effect within the enterprise and a positive effect among multinational companies. Huang and Kim (2019) studied the spillover effect of the competition of downstream enterprises in the supply chain on the capital structure decision of upstream enterprises and reported that the competitive behavior of downstream customers had a greater effect on the capital composition of upstream suppliers.

Network theory emphasizes the interconnection and dependence between different entities in the supply chain network. The spillover effect is usually caused by the interconnection between enterprises in the supply chain. For example, suppliers may adopt new technologies or practices, and through direct or indirect relationships (such as buying houses, competitors, and even customers), this innovation is spread throughout the supply chain. Some studies have investigated the spillover effect of enterprise technology application in the supply chain. Zhang, Min Du, and Lin (2025) explained that the digitalization of customers promotes the spillover effect of suppliers from the perspective of supply chain spillover. Network theory suggests that the status of enterprises in the supply chain network enables their technology and capabilities to spread to other enterprises in the network through formal cooperation and informal knowledge-sharing practices (Nwafor et al. 2023).

The resource-based view emphasizes that when an enterprise's resources or capabilities have an impact on the broader supply chain, it will produce spillover effects. Mao and Guo (2025) reported that customers' robot adoption optimized the employment structure of supplier enterprises through a positive information spillover effect. When leading enterprises in the supply chain develop new technologies or operational capabilities, the resources may overflow to other companies in the network through direct transfer, imitation, or collaboration (Geng et al. 2024).

The above studies focus on the impact of the supply chain spillover effect on knowledge and technology diffusion and lack research on enterprise operation interactions in the supply chain. This study provides a new research perspective by exploring the vertical transmission of the process by which robot adoption affects supply chain resilience among supply chain enterprises.

This work builds on Pettit et al.'s (2010) resilience framework by exploring supply chain resilience from a dynamic capabilities perspective, which helps to understand how enterprises can withstand disruption and thrive and adapt to the changing environment, ensuring a balance between capability and vulnerability. While existing research has explored various dimensions of resilience, few studies have systematically examined how the adoption of industrial robots influences firms' ability to reconfigure resources and maintain operational continuity under volatility. In particular, the role of robot adoption in enhancing firms' risk resilience under the moderating influence of corporate strategy remains insufficiently explored in empirical research.

Moreover, current literature offers limited insight into the network-level implications of robot adoption. Little attention has been paid to how technological upgrades in focal firms may generate spillover effects that influence the resilience of upstream and downstream partners within supply chain networks. This omission restricts our understanding of the broader organizational and interorganizational dynamics through which resilience is developed and diffused. To address these gaps, this study integrates firm-level adoption behavior with supply chain network data and introduces a novel resilience measurement approach rooted in dynamic capabilities theory. This enables a more granular and relational understanding of resilience development in technologically evolving supply chains.

2.4 | Research Hypotheses

Building on Richey Jr. et al. (2023)'s exploration of the influence of artificial intelligence—particularly industrial robots—on supply chain management, this study extends the discussion by hypothesizing that robot adoption enhances supply chain resilience. On the basis of prior research, robot adoption enhances supply chain resilience through the following three main channels: improving resource control (Koch and Manuylov 2023), boosting operational efficiency (Antonioli et al. 2024), and fostering collaborative governance (Matthews et al. 2025). First, the resource-based view theory holds that industrial robots are valuable resources that enable enterprises to allocate human and material resources more effectively (Koch and Manuylov 2023). The adoption of robots has strengthened the enterprise's control over resources, elevated its position in the supply chain, and improved its ability to manage supply crises (Maghazei et al. 2022), thereby enhancing the resilience of the supply chain. Additionally, competitive advantage theory holds that robot adoption can increase product differentiation in the supply chain, strengthening competitiveness and market share (Cilekoglu et al. 2024). Second, according to the resource-based view, robots reduce labor demand, helping companies save operating costs and optimize expenses and thereby increasing operational efficiency (Feigenbaum and Gross 2024). Chen et al. (2023) reported that human resource redundancy negatively impacts supply chain resilience but that robot adoption mitigates this effect by optimizing human resources and improving long-term operational confidence. Finally, according to the technological innovation concept of innovation diffusion theory, the adoption of new technologies (such as industrial robots) can improve the internal process (Benhabib et al. 2021). Robot adoption facilitates intelligent and automated manufacturing, improving communication efficiency and internal control processes (Nikolova et al. 2024). By enhancing connections with upstream and downstream enterprises, robots improve control over the supply chain (Jia et al. 2024) and the level of adaptability to external environments (Acemoglu and Restrepo 2021). Robots also promote creativity, creating dynamic adaptability that strengthens supply chain resilience (Huang et al. 2024). Accordingly, we propose the following hypothesis:

H1. *Robot adoption enhances the supply chain resilience of enterprises.*

The digital transformation strategy has driven the implementation of robot adoption, and enterprises are using industrial robots more quickly to enhance information technologies such as artificial intelligence, blockchain, cloud computing, big data, and the IoT (Melzner et al. 2023; Sternberg et al. 2023). According to the resource-based view, these next-generation digital technologies can increase supply chain resilience by influencing supply chain management operations (Ciulli et al. 2020). Enterprise digital transformation can utilize digital technology to strengthen information sharing and action with upstream suppliers and downstream customers and redesign and plan supply chain structures and activities (Cao et al. 2022). Therefore, more promotion of digital transformation strategies by enterprises can promote the reconstruction of upstream and downstream partnerships in the supply chain through the adoption of industrial robots, improve governance structures, and enhance supply chain resilience.

H2a. *Enterprise digital transformation has a moderating effect on the relationship between robot adoption and supply chain resilience.*

The adoption of industrial robots can effectively increase the resilience of firms to external shocks by increasing automation, reducing human intervention, and enhancing responsiveness. However, relying on technological tools alone is not sufficient to achieve the desired resilience-enhancing effects, and the firm's innovation strategy may play a key moderating role. Based on the theory of resource dependence, firms cannot fully control the key resources they need on their own and must reduce the uncertainty and dependence on the external environment through strategic behavior (Wang et al. 2025). As a mechanism for integrating internal resources, acquiring new external resources, and enhancing organizational adaptability, innovation strategy can facilitate the synergistic integration of industrial robots with existing business processes, human structures, and supply chain networks when they are introduced into a company, thus maximizing the resilience return on technology investment (Birkel and Müller 2025). The innovation strategy enables companies to be more forward-looking and agile, to identify and respond to potential risks and obstacles in the adoption of industrial robots more effectively, and to enhance their path to value realization (Ahmadi et al. 2025). Further, from the perspective of dynamic capability theory, the key to a company's ability to build and maintain competitive advantage in a rapidly changing environment lies in its ability to sense, integrate, and reconfigure resources (Herburger et al. 2024). Innovation strategy reflects the ability of enterprises to perceive emerging technologies (e.g., industrial robots) and market changes and to promote the effective implementation of technology and organizational adaptation through resource reorganization and capability restructuring. In this process, enterprises are not only passively adopting technologies but also incorporating them into their innovation system, actively shaping their position and resilience in the supply chain. Therefore, corporate innovation strategy can strengthen the positive impact of industrial robot adoption on supply chain resilience. In summary, corporate innovation strategy, as an important mechanism for integrating resources and reshaping capabilities, may play a positive moderating role in the relationship between industrial robot adoption and corporate supply chain resilience. Based on this, the following hypotheses are proposed:

H2b. *The adoption of enterprise innovation strategies moderates the relationship between robot adoption and supply chain resilience.*

Since the supply chain network is a complete system, systems theory suggests that resilience at the supply chain network level is not an isolated phenomenon. There is a diffusion of interactions that influence resilience among firms (Alikhani et al. 2023). Network theory focuses on interactions between firms and supports the idea that interfirm relationships between firms in a supply chain can provide a buffer against disruptions and improve the ability of firms to cope with disruptions (Ge and Bao 2024). The resilience of focal firms can buffer against disruptions in upstream and downstream activities, creating a feedback loop that strengthens the entire system (Chen et al. 2025). Can corporate robot adoption affect the resilience performance of upstream and downstream partner firms? We therefore analyze the spillover effect of the relationship between robot adoption and supply chain resilience across the supply chain. We argue that the facilitating effect of robot adoption on supply chain resilience is reflected not only in the horizontal facilitation of organizational resilience by industrial robots within firms but also in the vertical enhancement of overall supply chain resilience through the adoption of industrial robots in the supply chain.

Enterprise robot adoption can form knowledge spillovers to downstream enterprises in the supply chain by providing a richer knowledge base and innovative skills, generating spillover benefits (Agrawal et al. 2020). Moreover, robot adoption can also enter downstream enterprises in the form of intermediate goods by improving products and proposing new product designs, helping downstream enterprises obtain spillover benefits (Nichols et al. 2019). Downstream enterprises can save more costs for management and innovation. Compared with demand spillover effects, Bianchi and Giorcelli (2022) argued that supply spillover effects are more easily absorbed and trigger long-term effects. Buyers can obtain spillover effects from suppliers, which in turn affect the cost-effectiveness and responsiveness of the supply chain (Dixit and Stiglitz 1977). The upstream robot adoption in the supply chain transmits this spillover effect to downstream customers through products (Baldwin and Lopez-Gonzalez 2015). Focal firms' industrial robot adoption can better help downstream customers adapt to supply chain environments and improve supply chain performance, which leads to the following hypothesis:

H3a. *Industrial robot adoption by focal firms can enhance the supply chain resilience of downstream partners.*

The demand-driven characteristics of the supply chain in the era of digital intelligence are increasingly prominent (Brau et al. 2023), thus enabling downstream enterprise robot adoption to provide stable and reliable customer sources for upstream enterprises through supply chain correlation, forming a backward spillover effect, optimizing the matching between supply and demand (Costello 2020), and thereby enhancing supply chain resilience. Chu et al. (2019) reported that when customers' new technology adoption is more in-depth, the backward spillover effect of the supply chain is more significant, suppliers and customers are closer in the field of technology, and the proximity of upstream and downstream enterprises has a greater effect on upstream enterprises. Therefore, the robot adoption of downstream enterprises can provide more development advantages for upstream enterprises. By leveraging this development advantage, the supply chain can adjust resource allocation and improve production efficiency. Compared with other effects, the adoption of industrial robots is more conducive to reducing inventory fluctuations in the supply chain, reducing supply and demand deviations, and providing a stable supply chain environment (Maghazei et al. 2022). This demand-driven feature can help upstream suppliers better plan production, reduce inventory fluctuations, and improve production efficiency (Sundaresan et al. 2023). Upstream suppliers can better optimize resource allocation, improve innovation capabilities, and achieve diversified and personalized development (Palepu 2023). Focal firms can provide a better development environment for upstream suppliers by improving the demand-driven supply environment through robot adoption. Thus, we propose the following:

H3b. *Industrial robot adoption by focal firms can enhance the supply chain resilience of upstream partners.*

Figure 1 depicts the impact path of robot adoption on supply chain resilience and the research hypotheses.

3 | Methodology

To investigate how industrial robots affect supply chain resilience, this study creates an economic regression model. A combination of traditional econometric benchmark regression models and the Johnson–Neyman approach (Johnson and Neyman 1936) is used to analyze the impact of industrial robot adoption on supply chain resilience, as well as the associated moderating effects. Specifically, we apply the following equation:

$$SCR_{i,t} = \alpha_0 + \alpha_1 Robot_{i,t} + \alpha_2 M_{i,t,k} + \alpha_3 M_{i,t,k} Robot_{i,t} + \alpha_n Controls_{i,t} + Time/Industry\ FE + \varepsilon_{i,t} \tag{1}$$

where i and t denote the firm and time, respectively. *Controls* is the control variable. *Time / Industry FE* indicates that our model considers both time and industry fixed effects. The error term is defined as $\varepsilon_{i,t}$.

3.1 | Dependent Variable

The dependent variable is supply chain resilience (*SCR*). Pettit et al. (2010) proposed a resilience assessment framework and developed it as a measurable method for evaluating the balance between two factors in enterprise supply chain resilience assessment.

On the basis of the conceptual framework of capability-vulnerability balance for supply chain resilience proposed by Pettit et al. (2010), we extract the capability and vulnerability factors from the framework and organize them into a Chinese vocabulary of enterprise supply capability and vulnerability keywords. The generated Chinese word library is then manually filtered and annotated to obtain a new word library with complete semantics and in accordance with Chinese word formation rules. Finally, the new word library is submitted to relevant experts for secondary filtering to obtain a Chinese lexicon of supply chain capability and vulnerability keywords.

To measure the balance between capability and vulnerability factors, Cao et al. (2009) distinguished the relationship between two variables as binary balance and binary combination. Binary balance is defined operationally through differencing, but the form of differencing is a mechanical measure of equilibrium that cannot verify the equilibrium relationship between two variables that are independent or interact with other variables. Mathias et al. (2018) proposed the concept of organic balance by emphasizing the balance relationship of binary variables under

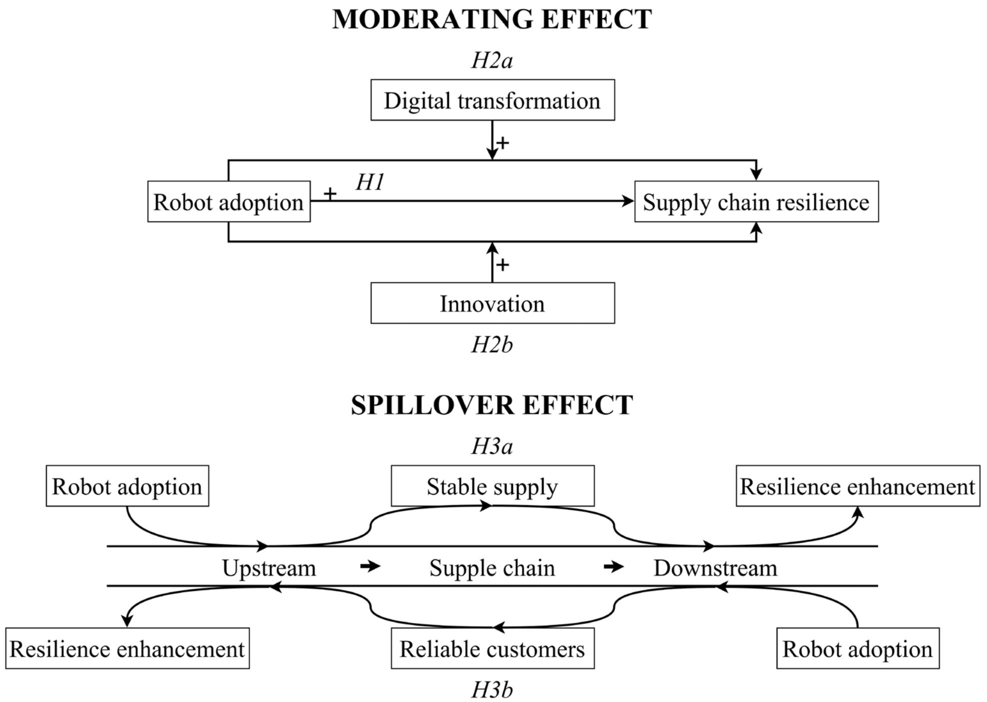

FIGURE 1 | Hypothesized research model.

balance matching. The balance of two variables is established on the basis of their orthogonal combination. This study utilizes the binary organic balance measurement method proposed by Mathias et al. (2018) to assess the balance between an enterprise's supply capacity and its vulnerability. The formula is as follows:

$$SCR = 1 - \frac{|x - y|}{(x + y)} \tag{2}$$

where SCR represents the balance between the supply capacity and vulnerability of the enterprise, that is, the resilience of the enterprise's supply chain, and where x and y represent the scores of the capability factor and vulnerability factor, respectively. Both x and y were obtained from text analysis, expressed in terms of keyword frequencies.

3.2 | Independent Variable

Robot is a proxy variable for robot adoption, represented by the natural logarithm of robot penetration, which is the main independent variable of this paper. Acemoglu and Restrepo (2020) constructed a measure of robot penetration at the regional level in the United States on the basis of a general equilibrium model, which is measured as follows:

$$RobotP_{jt} = \frac{RobotStock_{jt}}{Labor_{jt=2010}} \tag{3}$$

where $RobotP_{jt}$ represents robot penetration in industry j at time t, $RobotStock_{jt}$ represents robot stock in industry j at time t, and $Labor_{jt=2010}$ represents employment figures for industry j in 2010 (base year). The reason for choosing 2010 employment data in this article is as follows. First, when constructing the robot penetration variable, Acemoglu and Restrepo (2020) chose to use 1990 United States employment data by industry because the United States gradually began to apply industrial robots in the early 1990s. China's use of robots began to grow rapidly in 2010, and the application level of robots in 2010 was comparable to that in the United States in 1990. Second, 2010 was earlier than the sample study period in this study, which can to some extent avoid the endogeneity problem of the model.

Although stock data on robots by nation and industry are available in the International Federation of Robotics (IFR) database, the proportionate contribution of robot adoption at the firm level cannot be adequately represented by the absolute stock information at the industry level. According to Caselli et al. (2025), this study uses the basic idea of Bartik instrumental variables to analyze the effects of robot penetration from the industry level to the firm level (Bartik 1991), computed as follows:

$$RobotFP_{ijt} = \frac{Labor_{ijt=2010}}{Manulab_{jt=2010}} \times RobotP_{jt} \tag{4}$$

This indicator measures the level of robot penetration for firm i in industry j at time t. $Manulab_{jt=2010}$ is the median number of employees in all companies in industry j in 2010 (base year). The ratio of firm i's employee share in industry j's production sector in 2010 (base year) to the median share of all companies in industry j's production sector in 2010 (base year) is represented as $\frac{Labor_{ijt=2010}}{Manulab_{jt=2010}}$. The independent variable *Robot* in Equation (1) is expressed using the natural logarithm of the firm's robot penetration, i.e., $Robot = \log(RobotFP)$.

3.3 | Moderating and Control Variables

$M_{i,t,k}$ represents the kth moderating variable for firm i in year t. k takes the value of $\{0,1\}$, with $M_{k=0}$ and $M_{k=1}$ representing innovation (*Ino*) and digital transformation (*DT*), respectively. *Ino* indicates that the degree of implementation of an enterprise's innovation strategy is the size of the enterprise's R&D activities, expressed in the number of patents. The number of patents of enterprises represents innovation investment and intellectual property accumulation in the technology field of enterprises and is an objective way to quantify the R&D activities of enterprises. The greater the number of patents, the more inclined the enterprise is to the innovation strategy (Acemoglu and Restrepo 2020). *DT* represents the digital transformation proxy variable, which uses text analysis to determine the frequency of keywords related to digitization (Bodrožić and Adler 2022; Nambisan et al. 2019). Enterprises with higher keyword frequencies are more inclined toward digital transformation strategies than are those with lower keyword frequencies. If α_3 is significant, the moderating effect of this variable is significant.

In the benchmark regression, our main focus is on the coefficient α_1 in Equation (1), which shows how robot adoption affects supply chain resilience. A group of control factors known as *Controls* are thought to be crucial for a firm's *SCR*. The natural logarithm of the total number of employees plus one is employed to calculate *Size*. A firm's *Age* is its age. The selection of *Size* and *Age* mainly refers to Jiang et al. (2025) to reflect the basic characteristics of the firm. Femano and Breitbach (2025) suggest that firms' financial performance and operating conditions also affect supply chain resilience. We therefore introduce income growth rate and debt level as control variables. The operational income growth rate is denoted by *Growth*. *Debt* can be calculated by dividing the entire debt of the enterprise by its total assets. Since Xu et al. (2024) chose shareholding characteristics as a control variable for supply chain resilience research based on the perspective that board characteristics can affect intra-firm decision-making and strategic choices. Board characteristics, including the number of board members (*BM*), board salary (*BS*), and female director ratio (*FDR*), are also considered in this paper.

3.4 | Data Sources

A 2022 report from the IFR revealed that China now leads the world with over 1.5 million industrial robots in use, maintaining its position as the world's largest market for industrial robots since 2013. So, it is more representative to study the development status of robot adoption and enterprise supply chain resilience in China. This study uses Chinese listed companies that were active between 2013 and 2022, with data mostly from three sources. The selection of manufacturing enterprises is based on the national standard GB/T 4754–2017 Classification of National Economic Industries. The IFR 2023 Industrial Robotics Report contains robot inventory and installation statistics broken down by industry, nation, and time. These data are relevant to industrial robots. The study constructs the core explanatory variable, Chinese firms' robot penetration, according to Equation (3), to measure the extent of robot adoption by Chinese listed firms. The data for listed firms are drawn mainly from the China Stock Market & Accounting Research Database (CSMAR), which contains relevant indicators of operational efficiency, the gearing ratio, firm type, firm size, the revenue growth rate, firm year, the number of enterprise patents, and other relevant data. Cumulative data on patents granted to listed firms is disclosed in the CSMAR, which contains both invention and utility model patents, and we use this data to construct an indicator of firms' innovation strategies. In addition, industry-level employment data were obtained from the China National Bureau of Statistics (https://data.stats.gov.cn/). The study manually matches and then forms a set of firm-industry-year statistics.

We standardized China's two-digit industry classification codes to the 2011 standard using the files of the International Standard Industrial Classification of All Economic Activity Revision 4 and GB/T 4754–2011 due to disparities in industry classifications within the data of robot utilization in the IFR and the information of listed firms. Afterward, we compare them with the IFR industry robot stock information. We obtain balanced panel data totaling 2900 samples from 290 Chinese listed companies. Table 1 presents the descriptive statistics.

The supply chain capacity indicator (x), vulnerability indicator (y) and digital transformation (DT) are expressed as the frequency of keywords in the enterprise's annual financial report (AFR) obtained through the Wingo database (www.wingodata.com) using the Chinese lexicon of the above keywords.

4 | Results

4.1 | Robot Adoption and Supply Chain Resilience

The correlation test results are shown in Table 2. The analysis provides preliminary evidence in favor of our theory, demonstrating a significant positive association between robot adoption and supply chain resilience. Additionally, the variance inflation factor (VIF) score of the multicollinearity test is 1.01, which is below the 10-point cutoff. This finding suggests that the model does not contain any significant multicollinearity.

We then perform a within-group autocorrelation test. It is hypothesized that there is no first-order autocorrelation within the group. According to the Wooldridge test for panel data autocorrelation, $P > F = 0.000$. Therefore, there is no within-group autocorrelation in these panel data. Thereafter, we perform a baseline regression.

We use regression that considers both time and industry fixed effects to examine how robot adoption affects an enterprise's supply chain resilience. Table 3 shows the benchmark regression results. Column (1) shows the results of univariate regression, which evaluates the impact of robot adoption on supply chain resilience. Column (2) considers a one-year lag based on univariate regression, which better illustrates this impact. The control variable described in Section 3 is added to column (3). Column (4) shows the results of using robust standard error regression to address the potential heteroscedasticity issue.

The regression coefficients of the predicted level of robot adoption on supply chain resilience are 0.042, 0.053, 0.046, and 0.046, respectively. All these values are significant at the 1% level. Overall, the estimation results indicate that the adoption of robots by enterprises promotes their supply chain resilience. The hypothesis in Section 2 that robot adoption can enhance the supply chain resilience of enterprises is verified. Our research findings support previous studies that have emphasized the role

TABLE 1 | Descriptive statistics.

	Variable	Obs.	Mean	Std. dev.	Min	Max	Source
Dependent variable	SCR	2900	0.62	0.14	0.01	0.95	AFR
Independent variable	Robot	2900	0.95	1.75	−3.75	4.12	IFR
Control variables	Size	2900	3.59	0.71	0.30	5.65	CSMAR
	Age	2900	18.61	5.34	3	38	CSMAR
	Growth	2900	0.19	1.36	−0.96	45.82	CSMAR
	Debt	2900	0.55	0.61	0.02	29.70	CSMAR
	BM	2900	9.46	2.12	5	21	CSMAR
	BS	2900	6.13	1.04	0	7.76	CSMAR
	FDR	2900	0.29	0.19	0	1	CSMAR
Moderating variables	Ino	2900	15.79	30.63	0	336	CSMAR
	DT	2900	0.80	1.17	0	4.94	AFR

TABLE 2 | Correlation test.

	SCR	Robot	Size	Age	Growth	Debt	BM	BS	FDR	Ino	DT
SCR	1.000										
Robot	0.171***	1.000									
Size	0.337***	0.061***	1.000								
Age	0.298***	0.014	−0.002	1.000							
Growth	0.020	−0.052***	−0.021	0.022	1.000						
Debt	0.102***	−0.006	0.069***	0.040**	−0.000	1.000					
BM	0.317***	0.066***	0.159***	0.077***	−0.009	0.070***	1.000				
BS	0.162***	−0.029	0.013	0.105***	0.008	0.033*	0.154***	1.000			
FDR	0.100***	−0.099***	−0.151***	0.207***	0.010	−0.002	−0.156***	0.088***	1.000		
Ino	−0.014	0.316***	0.101***	−0.095***	−0.030	−0.022	−0.063***	−0.027	−0.073***	1.000	
DT	0.433***	−0.058***	0.126***	0.176***	−0.015	0.010	0.056***	0.100***	0.107***	0.148***	1.000

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

of intelligent technologies, such as robotics, in promoting supply chain development.

In columns (1) and (2), the results of adding lag are still robust, but the influence of other factors cannot be ruled out. Therefore, for calculation convenience, its lag is temporarily ignored in this study. According to the analysis of the control variables in columns (3) and (4), robot adoption is indeed the most important factor affecting an enterprise's supply chain resilience. In addition, board members have a significant effect on an enterprise's performance in terms of supply chain resilience.

To ensure the reliability of this study, we conduct robustness tests via the generalized method of moments (GMM) approach and replacement variables, addressing the problem of endogeneity, the results of which are presented in the Appendix S1.

4.2 | Mechanism Test

Building on the benchmark regression results that confirm the positive impact of industrial robot adoption on firms' supply chain resilience, the subsequent analysis turns to examine the conditions under which this effect may vary. Specifically, we explore whether and how firm-level strategic orientations—namely, innovation strategy and digital transformation strategy—moderate the relationship between industrial robot adoption and supply chain resilience. These strategies represent critical organizational capabilities that can either amplify or constrain the resilience-enhancing effects of technological adoption. By introducing these moderating variables, we aim to uncover the contingent nature of the robot–resilience nexus and provide a more nuanced understanding of how internal strategic choices shape the benefits derived from industrial automation.

The regression results of the model in Equation (1) are shown in Table 4 for the two moderating variables. Columns (1) and (2) present the Johnson–Neyman regression results when innovation is used as the moderating mechanism, considering both time and industry fixed effects and robust standard errors to eliminate potential heteroskedasticity. Column (2) builds on column (1) by adding the control variables mentioned in Section 3. Conversely, columns (3) and (4) present the results of Johnson–Neyman regressions with digital transformation as the moderating mechanism. The results show that both innovation and digital transformation significantly and positively enhance the effectiveness of robot adoption.

As shown in Table 4, *DT* is significantly positive at the 1% level, indicating that digital transformation plays a positive moderating role in enhancing the resilience of enterprise supply chains through robot adoption. Digital transformation can stimulate the transformation of industrial robot adoption toward supply chain resilience. *Ino* is significantly positive at the 5% level, and the innovation strategy positively moderates the relationship between robot adoption and supply chain resilience. Enterprises can enhance the role of robot adoption in improving supply chain resilience by implementing innovative strategies.

TABLE 3 | Baseline results.

Dependent variable: SCR				
	(1)	(2)	(3)	(4)
Robot	0.042***		0.046***	0.046***
	(3.087)		(3.287)	(3.490)
L.Robot		0.053***		
		(2.999)		
Size			5.034	5.034
			(0.288)	(0.290)
Age			3.767	3.767
			(1.333)	(1.429)
Growth			−3.353	−3.353
			(−0.396)	(−0.796)
Debt			−20.686	−20.686***
			(−1.085)	(−3.382)
BM			−12.648**	−12.648**
			(−2.071)	(−2.085)
BS			−0.416	−0.416
			(−0.037)	(−0.039)
FDR			79.095	79.095
			(1.201)	(1.211)
Constant	418.373**	496.167**	437.208***	437.208***
	(4.064)	(4.569)	(3.007)	(3.371)
Time FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
N	2900	2610	2900	2900
R-Squared	0.408	0.376	0.409	0.409

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

This study presents the Johnson–Neyman plot for testing the moderating effect of innovation, as shown in Figure 2. The length of the bold horizontal line indicates the range of values for robot adoption, that is, [−3.75, 4.12]. When the robot adoption values are outside the range [2.11, 4.12], the simple slope is $p < 0.05$, and the moderating effect of innovation is not significant. When enterprise robot adoption reaches a certain level, it is difficult for robot adoption to enhance supply chain resilience by stimulating innovation among enterprises. In the figure, in the area where the two vertical dashed lines overlap with the shaded area, namely, the pink shaded area, the confidence interval for the simple slope is 0. Outside this region, the simple slope is clearly nonzero. In the blue area, innovation plays a significant moderating role in the impact of robot adoption on supply chain resilience.

Moreover, this study presents the Johnson–Neyman plot for testing the moderating effect of digital transformation, as shown in Figure 3. When the robot adoption values are outside the range of [−5.36, 44.02], the simple slope is $p < 0.05$, and the moderating effect of digital transformation is not significant. The figure shows that in the pink shaded area to the left of the vertical dashed line, the confidence interval for the simple slope is 0. Outside this region, the simple slope is clearly nonzero. In the blue area, digital transformation plays a significant moderating role in the impact of robot adoption on supply chain resilience. The length of the bold horizontal line represents the range of values for robot adoption, that is, [−3.75, 4.12].

4.3 | Heterogeneity Analysis

We divide the sample into two subsamples on the basis of ownership and technological level to provide some evidence from a heterogeneity perspective. We study whether different enterprises with different ownership structures and industry technological developments perform differently in terms of the impact of robot

TABLE 4 | Moderating effect: Innovation strategy and digital transformation.

	Dependent variable: SCR			
	Innovation		Digital transformation	
	(1)	(2)	(3)	(4)
Robot	0.056**	0.056**	0.037***	0.038***
	(2.232)	(2.212)	(2.625)	(2.640)
Ino	−53.186	−50.018		
	(−1.488)	(−1.389)		
DT			1.094**	1.217**
			(2.327)	(2.559)
Robot*Ino	125.262**	117.759**		
	(2.297)	(2.143)		
Robot*DT			50.299***	48.426***
			(3.938)	(3.754)
Size		−33.716		−13.806
		(−1.097)		(−0.741)
Age		−0.131		4.142
		(−0.026)		(1.501)
Growth		16.613		−4.027
		(0.253)		(−0.885)
Debt		154.339		−20.124***
		(1.324)		(−3.451)
BM		−17.119		−14.902**
		(−1.571)		(−2.437)
BS		0.692		−6.253
		(0.047)		(−0.587)
FDR		−51.476		69.699
		(−0.474)		(1.030)
Constant	−460.379	−212.838	74.520	216.021
	(−1.561)	(−0.566)	(0.634)	(1.369)
Time FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
N	2900	2900	2900	2900
R-Squared	0.317	0.315	0.420	0.421

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

adoption on supply chain resilience. Choosing enterprise ownership and technological level as classification criteria can provide a deeper understanding of how different enterprises use robots to improve supply chain resilience. These two standards are directly related to operational flexibility, resource control, and innovation capability, which are key factors in achieving supply chain resilience (Cohen et al. 2022). These differences help reveal the heterogeneity of how different types of enterprises adopt industrial robots to increase supply chain resilience.

4.3.1 | Heterogeneity Analysis: State-Owned Enterprises (SOEs) and Non-SOEs

If the government is the ultimate controller of the enterprise, then we refer to the enterprise as an SOE; if not, then we refer to it as a non-SOE. SOEs can rely on government backstops and financial support to obtain more stable and abundant resources, making SOEs more effective at developing and implementing large-scale projects than non-SOEs are. Moreover, SOEs, as the

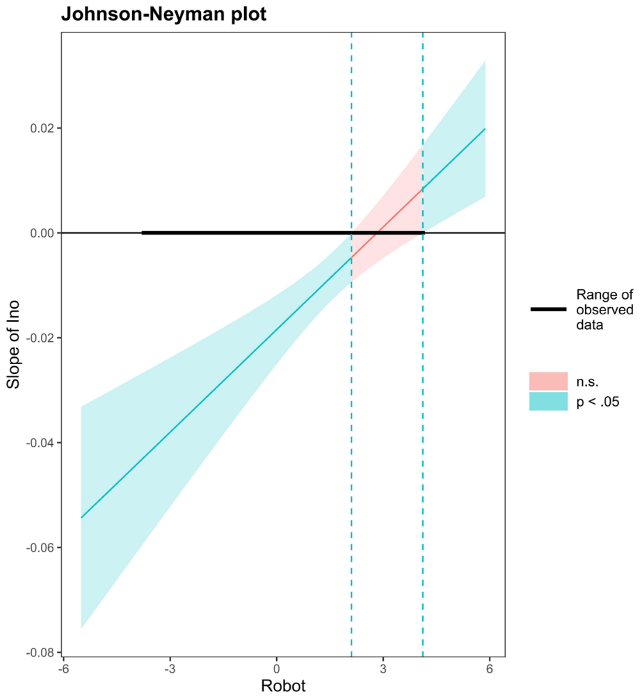

FIGURE 2 | Johnson–Neyman diagram of the moderating effect of innovation.

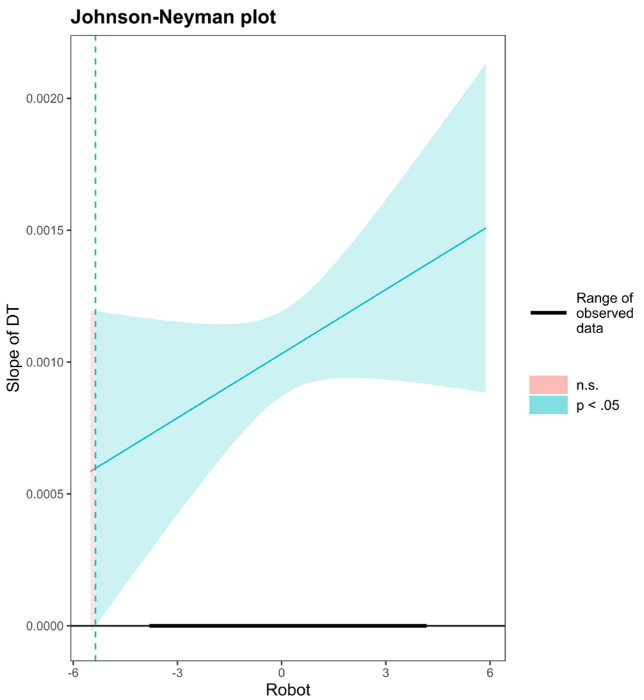

FIGURE 3 | Johnson–Neyman diagram of the moderating effect of digital transformation.

main bearers and leaders of strategically important national industries, can lead the development direction of the entire industry. There is often an advantage to having a more complete supply chain.

According to the resource-based view, the resources available to an enterprise determine its ability to adopt and utilize technology. SOEs typically receive significant government support, subsidies, and stable financing, which may provide them with the financial resources and political support needed to invest in and adopt expensive technologies such as industrial robots. On the other hand, non-SOEs may rely more on private capital and need to demonstrate the rationality of their investments with clear investment return rates, increasing their cost sensitivity. Institutional theory suggests that SOEs are often subject to political and regulatory pressures that affect their strategic decision-making. For example, SOEs may adopt robots not only to improve their operational efficiency but also to meet government requirements, industrial policies, or national development goals. In contrast, non-SOEs may place more emphasis on improving their competitive advantage, profitability, and agility, with a focus on technology-driven innovation. Stakeholder theory suggests that the governance structures of SOEs and non-SOEs are often different, with SOEs facing more bureaucratic control and public accountability, whereas non-SOEs typically have greater flexibility in their decision-making processes, which may affect their adoption patterns of industrial robots.

The data for SOEs and non-SOEs come from the China Stock Market & Accounting Research (CSMAR) database. The CSMAR database includes a variable indicating the nature of corporate ownership, which directly distinguishes between SOEs and non-SOEs. The classification of ownership type is determined based on the identity of the ultimate controlling shareholder. Enterprises whose shares are held by state-owned legal entities are categorized as SOEs, while others are non-SOEs. Table 5 shows the estimated results of the different impacts of robot adoption on SOEs and non-SOEs. The positive impact of robot adoption on the supply chain resilience of SOEs is significant and clearly positive. The impact on non-SOEs is not significant; thus, further research is needed to determine whether robot adoption has an impact on non-SOE supply chain resilience. The research results indicate that robot adoption has a more significant effect on improving supply chain resilience in SOEs than in non-SOEs.

Compared with non-SOEs, SOEs are more likely to further develop their supply chain resilience after accepting robot adoption because of their advantages in self-generated supply chain development. The basic conditions for non-SOEs to develop their supply chains are relatively limited, and the adoption of robots may not necessarily successfully promote their supply chain development. Therefore, it is necessary to accelerate the improvement in institutional rules for cooperation between SOEs and non-SOEs, continue to carry out coordinated development and deepen cooperation between SOEs and non-SOEs, guide SOEs in building a collaborative and win–win supply chain ecology, and promote improvements in non-SOE supply chain resilience.

4.3.2 | Heterogeneity Analysis: High-Tech and Low-Tech Industries

The technological sophistication of an enterprise's operation affects its ability to use advanced industrial robots to increase the resilience of the supply chain.

TABLE 5 | Heterogeneity: Firms' ownership.

	Dependent variable: SCR			
	SOEs		Non-SOEs	
	(1)	(2)	(3)	(4)
Robot	0.003**	0.007***	−0.002	−0.003
	(2.179)	(3.473)	(−0.763)	(−0.849)
Size		−0.003		−0.009
		(−0.715)		(−1.290)
Age		0.000		0.003***
		(0.265)		(3.040)
Growth		−0.009		0.000
		(−1.264)		(0.196)
Debt		−0.044***		−0.001
		(−2.835)		(−0.664)
BM		−0.002*		0.001
		(−1.927)		(0.527)
BS		0.001		0.006
		(0.413)		(0.989)
FDR		0.035**		−0.030
		(2.494)		(−1.354)
Constant	0.529***	0.575***	0.405***	0.357***
	(39.168)	(20.354)	(17.241)	(7.404)
Time FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
N	1980	1980	920	920
R-Squares	0.388	0.394	0.373	0.376

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

TABLE 6 | Heterogeneity: Industry technology level.

	Dependent variable: SCR			
	Firms in high-tech industries		Firms in low-tech industries	
	(1)	(2)	(3)	(4)
Robot	0.003***	0.007***	0.000*	0.002
	(2.880)	(2.741)	(1.869)	(1.638)
Size		0.005		−0.006
		(1.049)		(−1.187)
Age		−0.001		0.002***
		(−1.286)		(3.220)
Growth		0.001		−0.001
		(0.948)		(−0.360)
Debt		−0.029		−0.003***
		(−1.480)		(−3.599)
BM		−0.003*		−0.001
		(−1.905)		(−0.507)
BS		−0.004**		0.005**
		(−2.025)		(2.180)
FDR		0.055***		−0.043**
		(3.610)		(−2.428)
Constant	0.414***	0.452***	0.432***	0.423***
	(28.770)	(15.944)	(21.534)	(12.631)
Time FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
N	1320	1320	1580	1580
R-Squared	0.336	0.346	0.365	0.370

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

We classified the sample of listed manufacturing enterprises according to the Classification Catalog of High-Tech Industry Statistics revised by the National Bureau of Statistics in 2017. According to the Classification of High-Tech Industries (Manufacturing) (2017), high-tech industries can be classified into six categories: pharmaceutical manufacturing, aviation, spacecraft and equipment manufacturing, electronic and communication equipment manufacturing, computer and office equipment manufacturing, medical equipment and instrument manufacturing, and information chemical manufacturing. The remaining enterprises are low-tech enterprises.

We propose that whether a firm is a high-tech firm, i.e., the technological sophistication of a firm, affects its ability to use advanced industrial robots to increase supply chain resilience. According to the technology acceptance model, the degree of difficulty for enterprises in accepting new technologies and integrating them into operations is affected by their perceptions of usefulness and ease of use. High-tech enterprises usually prefer to adopt advanced robots because they already have the technical skills, infrastructure, and innovation culture required to absorb and optimize new technologies. In contrast, low-tech enterprises may need more time and investment to train employees, modify existing infrastructure, and integrate new technologies into their operations. By classifying enterprises according to their technological level, this study can analyze how innovation capability, adoption speed, and robot integration affect the ability of enterprises to improve the resilience of the supply chain. Table 6 shows the results of industrial technology heterogeneity.

Table 6 shows that, as shown in the first two columns, the predictive coefficient of robot adoption promoting supply chain resilience in high-tech industries is quite positive and significant at the 1% level. However, the correlation between the robot coefficient and low-tech enterprises is relatively small. Overall, the research findings suggest that high-tech industries are more sensitive to the effects of robot adoption on supply chain resilience, with increased robot adoption being more likely to enhance resilience in high-tech industries than in low-tech industries.

5 | Spillover Effects in the Supply Chain

This study refers to the upstream and downstream enterprise matching methods of Isaksson et al. (2016) to study the vertical transmission mechanism of enterprise robot adoption in the supply chain and constructs a dataset of robot adoption enterprises and upstream and downstream interactive enterprises annually. With the help of this dataset, this work uses fixed effects regression to study the spillover effects of enterprise robot adoption in the supply chain.

This study uses active Chinese listed manufacturing companies from 2013 to 2022 as the sample and obtains basic information on the top five customers and suppliers of listed companies from the CSMAR database. Owing to the possibility of multiple customers (C1, C2, and C3) or suppliers (S1, S2, and S3) in the observation object (A), this work constructs multiple samples, including A-C1-2022, A-C2-2022, A-C3-2022, A-S1-2022, A-S2-2022, and A-S3-2022. After excluding samples from nonlisted companies, financial industries, and special treatment (ST) and ST* companies and removing samples with missing variables, a total of 1705 observations from upstream listed companies and 2493 observations from downstream listed companies are obtained.

When conducting benchmark regression research, referring to the regression methods of Isaksson et al. (2016), when studying the positive spillover effects of the supply chain, the dependent variable is the supply chain resilience of downstream customer enterprises, and the independent variable is the robot adoption proxy variable of the observed enterprise. The relevant data from downstream customer enterprises are selected as control variables. The backward spillover effect is similar and replaces only the relevant variables with data from upstream enterprises. Moreover, this regression considers time and individual fixed effects and incorporates robust standard errors to eliminate potential heteroscedasticity.

The regression results of the effects of the adoption of upstream enterprise robots on downstream customer enterprise supply chains are shown in Table 7. Column (2) adds control variables on the basis of the regression in column (1). Enterprise robot adoption has significantly improved the supply chain resilience of customer enterprises. Therefore, in the development of supply chain resilience, external spillover effects should be considered, and policy formulation should focus on the entire supply chain process. With respect to the topic of vertically promoting the development of supply chain resilience through robot adoption, it is necessary to fully recognize the interrelated effects across enterprises. The development of industrial robots and supply chain resilience should not only focus on an individual enterprise's own situation but also help other enterprises in the supply chain promote overall development.

TABLE 7 | Positive spillover effects of upstream enterprise robot adoption.

	Dependent variable: C.SCR	
	(1)	**(2)**
Robot	0.296***	0.259**
	(3.085)	(2.499)
C.Size		0.016
		(0.088)
C.Age		−0.000
		(−0.343)
C.Growth		−0.015
		(−0.301)
C.Debt		0.014
		(0.092)
C.BM		0.011
		(0.925)
C.BS		0.017**
		(2.782)
C.FDR		0.075
		(0.352)
Constant	−0.189	−0.352
	(−0.741)	(−0.438)
Time FE	Yes	Yes
Industry FE	Yes	Yes
N	2493	2493
R-Squares	0.949	0.969

Note: This table shows the impact of upstream enterprise robot adoption on downstream enterprise supply chain resilience. The independent variable *C. SCR* represents the supply chain resilience of downstream enterprises, whereas the dependent variable *Robot* is a proxy variable for the adoption of robots in upstream enterprises. *C. Size*, *C. Age*, *C. Growth*, *C. Debt*, *C. BM*, *C. BS* , and *C. FDR* represent the size, year, revenue growth rate, debt ratio, number of board members, board compensation, and proportion of female directors of downstream customer enterprises, respectively. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

As shown in Table 8, the adoption of robots by enterprises has a significant backward spillover effect, which promotes the supply chain resilience of upstream enterprises and is significant at the 1% level. The development of enterprises is influenced by customer enterprises, and the characteristics of supply chain demand orientation are obvious. Therefore, policymaking should fully leverage the leading role of downstream enterprises, incentivize them to take the lead in development, and drive overall supply chain resilience.

TABLE 8 | Backward spillover effect of downstream enterprise robot adoption.

	Dependent variable: S.SCR	
	(1)	(2)
Robot	0.124***	0.173***
	(3.519)	(3.626)
S.Size		0.137
		(0.967)
S.Age		0.000
		(0.058)
S.Growth		−0.059
		(−0.682)
S.Debt		0.057
		(0.253)
S.BM		0.016
		(1.659)
S.BS		0.006
		(0.536)
S.FDR		−0.027
		(−0.165)
Constant	0.256**	−0.753
	(2.493)	(−1.059)
Time FE	Yes	Yes
Industry FE	Yes	Yes
N	1705	1705
R-Squared	0.872	0.869

Note: This table shows the impact of downstream enterprise robot adoption on upstream enterprise supply chain resilience. The independent variable *S. SCR* represents the supply chain resilience of upstream enterprises, whereas the dependent variable *Robot* is a proxy variable for downstream enterprise robot adoption. *S. Size*, *S. Age*, *S. Growth*, *S. Debt*, *S. BM*, *S. BS*, and *S. FDR* represent the size, year, revenue growth rate, debt ratio, number of board members, board compensation, and proportion of female directors of upstream supplier enterprises, respectively. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

6 | Conclusions

This study utilizes panel data from listed manufacturing companies in mainland China to investigate the link between robot adoption and supply chain resilience over a 10-year period (2013–2022). There is evidence suggesting that robot adoption can improve supply chain resilience. In addition, the implementation of enterprise innovation strategies and digital transformation can positively regulate this beneficial impact, and supply chain diffusion effects can spread this impact to upstream and downstream enterprises. In addition, our research reveals heterogeneity in corporate performance, with SOEs and high-tech industries experiencing significant positive impacts from robot adoption. This research can serve as a theoretical foundation for promoting the adoption of enterprise robots and strengthening supply chain resilience.

Our study contributes to the existing knowledge in various aspects. We contend that robot adoption can significantly enhance supply chain resilience. Our research findings contribute to the existing knowledge by illuminating the impact of robot adoption on supply chain resilience.

First, we investigate the adjustment mechanism influencing the impact of robot adoption on supply chain resilience. Innovation and digital transformation are important moderating mechanisms for regulating the resilience development of robot-driven supply chains. Our research suggests that digital transformation and innovation can help expand the benefits of robot adoption.

Second, heterogeneity analysis is conducted on the sample of listed companies from the perspectives of ownership type and technological level. According to observations, robot adoption has a more significant effect on the supply chain resilience of high-tech industries and SOEs than on that of low-tech industries and non-SOEs. SOEs are more likely to further develop their supply chain resilience after robot adoption because of their advantages in terms of self-generated supply chain development. The basic conditions under which non-SOEs develop their supply chains are relatively limited, and the adoption of robots may not necessarily successfully promote their supply chain development. In enterprises in high-tech industries, robot adoption greatly affects their productivity, leading to greater participation in the supply chain. Enterprises are more adaptable to the supply chain environment and have more say in the supply chain, further promoting stronger resilience performance in the supply chain.

Third, this study confirms that the positive impact of robot adoption on supply chain resilience extends across the entire supply chain. On the one hand, enterprise robot adoption can provide a stable supply for downstream customer enterprises. Robot adoption can generate technology and knowledge spillovers to downstream customer enterprises through the supply chain network, thereby enhancing their supply chain performance. On the other hand, increasing enterprise robot adoption can also promote the supply chain resilience of upstream suppliers. Through robot adoption, downstream enterprises can provide more accurate demand information to upstream suppliers, and the supply chain can achieve diversified and personalized development, which is conducive to highlighting the advantages of the supply chain itself.

6.1 | Theoretical Contributions

This study contributes to research on the impact of supply chain resilience in the context of robot adoption from an enterprise-level perspective. Research on supply chain resilience reveals clear limitations when viewed from this microlevel perspective. Given the widespread popularity of robot adoption in the Chinese industrial market, whether robot adoption can become a driving force for improving enterprise performance has become an important topic of discussion in the academic community. How does robot adoption affect an enterprise's supply chain resilience in this scenario? Therefore, this study takes the perspective of enterprises and uses empirical data from domestic listed manufacturing companies from 2013 to 2022 as a sample to discuss whether robot adoption can enhance supply chain resilience, thus enriching the existing research.

Second, this work analyzes the spillover effects of robot adoption and their impact on overall supply chain resilience growth from the perspective of the relationship between upstream and downstream enterprises in the supply chain. As the essence of the supply chain is the relationship between upstream and downstream enterprises, the study of supply chain resilience must consider the spillover effects of enterprise behavior on the external supply chain. This study further considers the spillover effects of enterprise robot adoption on upstream and downstream enterprises from the perspective of vertical correlation in supply chain enterprises. The spillover effects in two directions, including the positive spillover effect of upstream enterprise robot adoption promoting downstream enterprise development and enhancing supply chain resilience and the backward spillover effect of downstream enterprise robot adoption driving supply chain development, are analyzed separately. This approach provides a new theoretical basis for understanding the spillover effects of enterprise robot adoption and the growth mechanism of supply chain resilience, thereby identifying directions for promoting policy optimization and guiding enterprises.

Finally, this study contributes to research on the mechanism of enhancing supply chain resilience from a governance perspective; supply chain resilience research has focused mainly on the effects of macro policies on supply chain network resilience, clarifying the macro growth path of supply chain network resilience (Grossman et al. 2024; Zhao et al. 2019). Some studies explore how new technologies empower supply chain improvement, with a greater emphasis on agile manufacturing, facilitating multiparty participation, and collaborative development (Blaettchen et al. 2025; Hastig and Sodhi 2020; Lee et al. 2020). This study verified the moderating effects of enterprise innovation strategy and digital transformation and investigated the spillover effects in the supply chain. From a governance perspective, a regulatory path has been developed from the inside out, enriching research on enhancing supply chain resilience mechanisms.

6.2 | Managerial Implications

From a management perspective, the resilience and dynamic development of the supply chain largely depend on whether it can adapt to the development of technology applications represented by robot adoption. Our research elucidates organizational learning and interaction at the enterprise level. When enterprise managers consider the adoption of robots from the perspective of supply chain development, that is, whether robot adoption conforms to the development path of the supply chain, we reveal several easily overlooked issues.

First, our empirical results indicate that robot adoption always promotes improvements in supply chain resilience. Our research strongly encourages robot adoption, and if the target of robot adoption is SOEs and high-tech companies, then this driving effect will be even more evident, which will help better develop supply chain resilience.

Second, companies should adaptively adopt robots on the basis of their own development status. The policy for managing the use of robots should be consistent with the current labor density, development, and demand level on the basis of the specific effectiveness indicators of the enterprise.

In addition, there are bidirectional spillover effects in robot adoption in the supply chain. While leveraging downstream enterprise demand to drive development, policymaking should also focus on the entire supply chain process and expand policy incentives for robot adoption and digital development in enterprises. The development of enterprises should pay more attention to their relationships with other supply chain enterprises. The development of industrial robots and supply chain resilience should not only focus on their own situation but also develop together with other enterprises in the supply chain. On this basis, we make the following recommendations: accelerate the improvement in institutional rules for cooperation among SOEs, non-SOEs, and other types of enterprises; continue to carry out coordinated development; deepen cooperation between SOEs and non-SOEs; guide SOEs in building a collaborative and win–win supply chain ecology; and promote improvements in non-SOE supply chain resilience.

6.3 | Policy Implications

When macroeconomic policies are formulated, it is necessary to consider the internal dynamics of microeconomic entities to ensure that policies respond to market competition and are accompanied by measures to address unforeseeable situations. To recognize the differences between industries and individual entities, policymakers should adjust their approaches to promote the development of supply chain resilience. Innovators, especially those with limited capabilities, benefit from structured support such as external R&D contracts to bridge the gap with leading innovators.

The heterogeneity of enterprises can affect the implementation and effectiveness of policies; thus, a meticulous approach is needed to consider the specific situation of the industry and the characteristics of individual enterprises, such as competitiveness, nature, and profitability. Focusing on disadvantaged enterprises can ensure comprehensive and fair policy benefits.

Policies must balance the complexity of the supply chain environment with the coevolution of technology, which requires ensuring a stable technological foundation and reasonable robot adoption to promote the development of diversified enterprise capabilities. Strategic transformation should be consistent with the reality and opportunities of the enterprise, especially in terms of innovation and digital transformation. Given the rapid pace of technological progress, there is an urgent need to develop policies that actively involve businesses in technology adoption. These policies should promote the transformation of technological capabilities into dynamic capabilities through innovation and facilitate the development of supply chain resilience.

Our research provides valuable insights for policymakers and business leaders, encouraging innovation and digital transformation for supply chain development. The development of task-oriented and open science policies to utilize new technologies is crucial for the economic restructuring of modern society.

6.4 | Limitations and Future Research

This study investigates the impact and mechanisms of enterprise robot adoption on supply chain resilience, offering a novel perspective on the drivers of resilience and contributing to the theoretical development of this field. It also provides practical insights for policymakers and business leaders. Nonetheless, several limitations should be acknowledged to guide future research.

First, the analysis focuses on domestically listed manufacturing firms, which, despite covering a range of regions and sectors, may not fully capture the diversity of supply chain structures, strategies, and resilience mechanisms present in global contexts. Expanding future research to include international firms operating under varied institutional, cultural, and industrial conditions would enhance the generalizability of the findings and offer insights into cross-border resilience patterns. Second, by treating manufacturing firms as a single category, the study may overlook important industry-specific dynamics. Since supply chain configurations, technology adoption practices, and resilience responses can differ markedly across industries, future studies should consider disaggregated, sector-level analyses to uncover more targeted and nuanced mechanisms, enabling more precise strategic and policy implications.

Acknowledgments

This work was supported by the National Natural Science Foundation of China (Nos. 72171122, 71934001 and 72171124).

Conflicts of Interest

The authors declare no conflicts of interest.

References

Acemoglu, D., and P. Restrepo. 2020. “Robots and Jobs: Evidence From US Labor Markets.” *Journal of Political Economy* 128, no. 6: 2188–2244. https://doi.org/10.1086/705716.

Acemoglu, D., and P. Restrepo. 2021. “Demographics and Automation.” *Review of Economic Studies* 89, no. 1: 1–44. https://doi.org/10.1093/restud/rdab031.

Agrawal, A., U. Mukherjee, and S. Muthulingam. 2020. “Does Organizational Forgetting Affect Quality Knowledge Gained Through Spillover?—Evidence From the Automotive Industry.” *Production and Operations Management* 29, no. 4: 907–934. https://doi.org/10.1111/poms.13137.

Ahmadi, T., A. F. Hesaraki, and J. P. M. Morsch. 2025. “Exploring IT-Driven Supply Chain Capabilities and Resilience: The Roles of Supply Chain Risk Management and Complexity.” *Supply Chain Management-An International Journal* 30, no. 1: 50–66. https://doi.org/10.1108/scm-11-2023-0561.

Alikhani, R., A. Ranjbar, A. Jamali, S. A. Torabi, and C. W. Zobel. 2023. “Towards Increasing Synergistic Effects of Resilience Strategies in Supply Chain Network Design.” *Omega* 116: 102819. https://doi.org/10.1016/j.omega.2022.102819.

Antonioli, D., A. Marzucchi, F. Rentocchini, and S. Vannuccini. 2024. “Robot Adoption and Product Innovation.” *Research Policy* 53, no. 6: 105002. https://doi.org/10.1016/j.respol.2024.105002.

Armstrong, B., and J. Shah. 2023. “A Smarter Strategy for Using Robots Automation Should Focus More on Flexibilliv Than on Productivity.” *Harvard Business Review* 101, no. 3–4: 35–42.

Baldwin, R., and J. Lopez-Gonzalez. 2015. “Supply-Chain Trade: A Portrait of Global Patterns and Several Testable Hypotheses.” *World Economy* 38, no. 11: 1682–1721. https://doi.org/10.1111/twec.12189.

Bartik, T. J. 1991. *Who Benefits From State and Local Economic Development Policies?* W.E. Upjohn Institute. http://www.jstor.org/stable/j.ctvh4zh1q.

Benhabib, J., J. Perla, and C. Tonetti. 2021. “Reconciling Models of Diffusion and Innovation: A Theory of the Productivity Distribution and Technology Frontier.” *Econometrica* 89, no. 5: 2261–2301. https://doi.org/10.3982/ECTA15020.

Bianchi, N., and M. Giorcelli. 2022. “The Dynamics and Spillovers of Management Interventions: Evidence From the Training Within Industry Program.” *Journal of Political Economy* 130, no. 6: 1630–1675. https://doi.org/10.1086/719277.

Birkel, H., and J. M. Müller. 2025. “Resilient by Nature or Technology? How Industry 4.0 Enhances Supply Chain Resilience Until 2035.” *Supply Chain Management: An International Journal* 30: 304–322. https://doi.org/10.1108/SCM-07-2023-0340.

Blaettchen, P., A. P. Calmon, and G. Hall. 2025. “Traceability Technology Adoption in Supply Chain Networks.” *Management Science* 71, no. 1: 83–102. https://doi.org/10.1287/mnsc.2022.01759.

Bodrožić, Z., and S. Adler. 2022. “Alternative Futures for the Digital Transformation: A Macro-Level Schumpeterian Perspective.” *Organization Science* 33, no. 1: 105–125. https://doi.org/10.1287/orsc.2021.1558.

Brau, R., J. Aloysius, and E. Siemsen. 2023. “Demand Planning for the Digital Supply Chain: How to Integrate Human Judgment and Predictive Analytics.” *Journal of Operations Management* 69, no. 6: 965–982. https://doi.org/10.1002/joom.1257.

Cao, Q., E. Gedajlovic, and H. Zhang. 2009. “Unpacking Organizational Ambidexterity: Dimensions, Contingencies, and Synergistic Effects.” *Organization Science* 20, no. 4: 781–796. https://doi.org/10.1287/orsc.1090.0426.

Cao, Q., X. Geng, and J. Zhang. 2022. “Impact of Channel Structure on a Manufacturer's Bundling Decision With an Application to Digital Goods.” *Production and Operations Management* 31, no. 4: 1679–1697. https://doi.org/10.1111/poms.13638.

Caselli, M., A. Fracasso, S. Scicchitano, S. Traverso, and E. Tundis. 2025. “What Workers and Robots Do: An Activity-Based Analysis of the Impact of Robotization on Changes in Local Employment.” *Research Policy* 54, no. 1: 105135. https://doi.org/10.1016/j.respol.2024.105135.

Chen, L., T. Li, F. Jia, and T. Schoenherr. 2023. “The Impact of Governmental COVID-19 Measures on Manufacturers' Stock Market Valuations: The Role of Labor Intensity and Operational Slack.” *Journal of Operations Management* 69, no. 3: 404–425. https://doi.org/10.1002/joom.1207.

Chen, Y., B. Li, and B. Huo. 2025. “Building Operational Resilience Through Digitalization: The Roles of Supply Chain Network Position.” *Technological Forecasting and Social Change* 211: 123918. https://doi.org/10.1016/j.techfore.2024.123918.

Chu, Y., X. Tian, and W. Wang. 2019. "Corporate Innovation Along the Supply Chain." *Management Science* 65, no. 6: 2445–2466. https://doi.org/10.1287/mnsc.2017.2924.

Cilekoglu, A. A., R. Moreno, and R. Ramos. 2024. "The Impact of Robot Adoption on Global Sourcing." *Research Policy* 53, no. 3: 104953. https://doi.org/10.1016/j.respol.2024.104953.

Ciulli, F., A. Kolk, and S. Boe-Lillegraven. 2020. "Circularity Brokers: Digital Platform Organizations and Waste Recovery in Food Supply Chains." *Journal of Business Ethics* 167, no. 2: 299–331. https://doi.org/10.1007/s10551-019-04160-5.

Cohen, M., S. Cui, S. Doetsch, et al. 2022. "Bespoke Supply-Chain Resilience: The Gap Between Theory and Practice." *Journal of Operations Management* 68, no. 5: 515–531. https://doi.org/10.1002/joom.1184.

Costello, A. M. 2020. "Credit Market Disruptions and Liquidity Spillover Effects in the Supply Chain." *Journal of Political Economy* 128, no. 9: 3434–3468. https://doi.org/10.1086/708736.

De Vito, A., M. Jacob, D. Schindler, and G. Xu. 2025. "How Do Corporate Tax Hikes Affect Investment Allocation Within Multinationals?" *Review of Finance* 29, no. 2: 531–565. https://doi.org/10.1093/rof/rfaf006.

Dixit, A., and J. E. Stiglitz. 1977. "Monopolistic Competition and Optimum Product Diversity." *American Economic Review* 67: 297–308.

Dixon, J., B. Hong, and L. Wu. 2021. "The Robot Revolution: Managerial and Employment Consequences for Firms." *Management Science* 67, no. 9: 5586–5605. https://doi.org/10.1287/mnsc.2020.3812.

Feigenbaum, J., and D. P. Gross. 2024. "Answering the Call of Automation: How the Labor Market Adjusted to Mechanizing Telephone Operation." *Quarterly Journal of Economics* 139, no. 3: 1879–1939. https://doi.org/10.1093/qje/qjae005.

Femano, A. L., and T. Breitbach. 2025. "Measuring Supply Chain Resilience for Informed Resilience Strategy Investment." *Transportation Journal* 64, no. 1: e12037. https://doi.org/10.1002/tjo3.12037.

Ge, R., and H. Bao. 2024. "Digital Transformation and Resilience of Supply Chain in Manufacture Listed Firms: A Backward Spillover Effects in the Vertical Supply Chain Relationship." *Finance Research Letters* 65: 105516. https://doi.org/10.1016/j.frl.2024.105516.

Geng, Y., X. Xiang, G. Zhang, and X. Li. 2024. "Digital Transformation Along the Supply Chain: Spillover Effects From Vertical Partnerships." *Journal of Business Research* 183: 114842. https://doi.org/10.1016/j.jbusres.2024.114842.

George, J., D. Whitten, R. Metters, and J. Abbey. 2022. "Emancipatory Technology and Developing-World Supply Chains: A Case Study of African Women Gemstone Miners." *Journal of Operations Management* 68, no. 6–7: 619–648. https://doi.org/10.1002/joom.1217.

Grossman, G. M., E. Helpman, and A. Sabal. 2024. "Optimal Resilience in Multitier Supply Chains." *Quarterly Journal of Economics* 139: qjae024. https://doi.org/10.1093/qje/qjae024.

Grover, A. K., and M. H. Ashraf. 2024. "Leveraging Autonomous Mobile Robots for Industry 4.0 Warehouses: A Multiple Case Study Analysis." *International Journal of Logistics Management* 35, no. 4: 1168–1199. https://doi.org/10.1108/IJLM-09-2022-0362.

Guedhami, O., A. Knill, W. L. Megginson, and L. W. Senbet. 2022. "The Dark Side of Globalization: Evidence From the Impact of COVID-19 on Multinational Companies." *Journal of International Business Studies* 53, no. 8: 1603–1640. https://doi.org/10.1057/s41267-022-00540-8.

Hastig, G. M., and M. S. Sodhi. 2020. "Blockchain for Supply Chain Traceability: Business Requirements and Critical Success Factors." *Production and Operations Management* 29, no. 4: 935–954. https://doi.org/10.1111/poms.13147.

Herburger, M., A. Wieland, and C. Hochstrasser. 2024. "Building Supply Chain Resilience to Cyber Risks: A Dynamic Capabilities Perspective." *Supply Chain Management: An International Journal* 29, no. 7: 28–50. https://doi.org/10.1108/SCM-01-2023-0016.

Huang, L. L., R. P. Chen, and K. W. Chan. 2024. "Pairing Up With Anthropomorphized Artificial Agents: Leveraging Employee Creativity in Service Encounters." *Journal of the Academy of Marketing Science* 52, no. 4: 955–975. https://doi.org/10.1007/s11747-024-01017-w.

Huang, Q., and R. Kim. 2019. "Capital Structure Decisions Along the Supply Chain: Evidence From Import Competition." *Journal of International Business Studies* 50, no. 6: 873–894. https://doi.org/10.1057/s41267-019-00225-9.

Isaksson, O. H. D., M. Simeth, and R. W. Seifert. 2016. "Knowledge Spillovers in the Supply Chain: Evidence From the High Tech Sectors." *Research Policy* 45, no. 3: 699–706. https://doi.org/10.1016/j.respol.2015.12.007.

Jia, F., Y. Xu, L. Chen, and K. Fernandes. 2024. "Does Supply Chain Concentration Improve Sustainability Performance: The Role of Operational Slack and Information Transparency." *International Journal of Operations & Production Management* 44, no. 10: 1831–1862. https://doi.org/10.1108/IJOPM-12-2022-0807.

Jiang, W., T. Feng, and C. Y. Wong. 2025. "How Big Data Analytics Capabilities Drive Supply Chain Resilience: The Mediating Roles of Supply Chain Visibility and Flexibility." *International Journal of Physical Distribution and Logistics Management* 55: 505–539. https://doi.org/10.1108/IJPDLM-07-2024-0252.

Johnson, P. O., and J. Neyman. 1936. "Tests of Certain Linear Hypotheses and Their Application to Some Educational Problems." *Statistical Research Memoirs* 1: 57–93.

Koch, M., and I. Manuylov. 2023. "Measuring the Technological Bias of Robot Adoption and Its Implications for the Aggregate Labor Share." *Research Policy* 52, no. 9: 104848. https://doi.org/10.1016/j.respol.2023.104848.

Koreis, J., D. Loske, and M. Klumpp. 2025. "Together, We Travel: Empirical Insights on Human-Robot Collaborative Order Picking for Retail Warehousing." *International Journal of Logistics Management* 36, no. 1: 1–20. https://doi.org/10.1108/IJLM-03-2023-0127.

Kude, T., J. Foerderer, S. Mithas, and A. Heinzl. 2023. "How Deadline Orientation and Architectural Modularity Influence Software Quality and Job Satisfaction." *Journal of Operations Management* 69, no. 6: 941–964. https://doi.org/10.1002/joom.1230.

Kumar, R. R., and A. Raj. 2025. "Big Data Adoption and Performance: Mediating Mechanisms of Innovation, Supply Chain Integration and Resilience." *Supply Chain Management: An International Journal* 30, no. 1: 67–85. https://doi.org/10.1108/SCM-03-2024-0186.

Lee, J., V. Krishnan, and H. Shin. 2020. "Business Models for Technology-Intensive Supply Chains." *Management Science* 66, no. 5: 2120–2139. https://doi.org/10.1287/mnsc.2019.3306.

Liu, H., S. Wei, W. Ke, K. K. Wei, and Z. Hua. 2016. "The Configuration Between Supply Chain Integration and Information Technology Competency: A Resource Orchestration Perspective." *Journal of Operations Management* 44: 13–29. https://doi.org/10.1016/j.jom.2016.03.009.

Maghazei, O., M. A. Lewis, and T. H. Netland. 2022. "Emerging Technologies and the Use Case: A Multi-Year Study of Drone Adoption." *Journal of Operations Management* 68, no. 6–7: 560–591. https://doi.org/10.1002/joom.1196.

Mao, Q., and C. Guo. 2025. "Industrial Robots, Supply Chain Spillover Effect and Firm Employment: Evidence From China." *Journal of Economic Behavior & Organization* 229: 106858. https://doi.org/10.1016/j.jebo.2024.106858.

Mateska, I., S. M. Wagner, and L. Stienen. 2024. "Media Reporting of Environmental Supply Chain Sustainability Risks: Contextual and

Moderating Factors." *Journal of Business Ethics* 199: 285–308. https://doi.org/10.1007/s10551-024-05759-z.

Mathias, B. D., A. F. Mckenny, and T. R. Crook. 2018. "Managing the Tensions Between Exploration and Exploitation: The Role of Time." *Strategic Entrepreneurship Journal* 12, no. 3: 316–334.

Matthews, M. J., R. K. Su, L. Yonish, S. McClean, J. Koopman, and K. C. Yam. 2025. "A Review of Artificial Intelligence, Algorithms, and Robots Through the Lens of Stakeholder Theory." *Journal of Management* 51: 2627–2676. https://doi.org/10.1177/01492063241311855.

Melzner, J., A. Bonezzi, and T. Meyvis. 2023. "Information Disclosure in the Era of Voice Technology." *Journal of Marketing* 87, no. 4: 491–509. https://doi.org/10.1177/00222429221138286.

Müller, J., K. Hoberg, and J. C. Fransoo. 2023. "Realizing Supply Chain Agility Under Time Pressure: Ad Hoc Supply Chains During the COVID-19 Pandemic." *Journal of Operations Management* 69, no. 3: 426–449. https://doi.org/10.1002/joom.1210.

Nambisan, S., M. Wright, and M. Feldman. 2019. "The Digital Transformation of Innovation and Entrepreneurship: Progress, Challenges and Key Themes." *Research Policy* 48, no. 8: 103773. https://doi.org/10.1016/j.respol.2019.03.018.

Negri, P. 2025. "Innovators and Transformers: Enhancing Supply Chain Sustainability: A Methodology Combining Dynamic Simulation and Case Studies." *International Journal of Physical Distribution and Logistics Management* 55: 409–425. https://doi.org/10.1108/IJPDLM-01-2024-0003.

Nichols, B. S., H. Stolze, and J. F. Kirchoff. 2019. "Spillover Effects of Supply Chain News on Consumers' Perceptions of Product Quality: An Examination Within the Triple Bottom Line." *Journal of Operations Management* 65, no. 6: 536–559. https://doi.org/10.1002/joom.1033.

Nikolova, M., F. Cnossen, and B. Nikolaev. 2024. "Robots, Meaning, and Self-Determination." *Research Policy* 53, no. 5: 104987. https://doi.org/10.1016/j.respol.2024.104987.

Nwafor, O., X. Ma, N. A. Johnson, R. Singh, and R. Aron. 2023. "Differential Impacts of Technology-Network Structures on Cost Efficiency: Knowledge Spillovers in Healthcare." *Journal of Management Information Systems* 40, no. 3: 840–882. https://doi.org/10.1080/07421222.2023.2229126.

Palepu, K. 2023. "How Should we Diversify Our Supply Chain?" *Harvard Business Review* 101, no. 11–12: 148–152.

Pettit, T. J., K. L. Croxton, and J. Fiksel. 2013. "Ensuring Supply Chain Resilience: Development and Implementation of an Assessment Tool." *Journal of Business Logistics* 34, no. 1: 46–76. https://doi.org/10.1111/jbl.12009.

Pettit, T. J., K. L. Croxton, and J. Fiksel. 2019. "The Evolution of Resilience in Supply Chain Management: A Retrospective on Ensuring Supply Chain Resilience." *Journal of Business Logistics* 40, no. 1: 56–65. https://doi.org/10.1111/jbl.12202.

Pettit, T. J., J. Fiksel, and K. L. Croxton. 2010. "Ensuring Supply Chain Resilience: Development of a Conceptual Framework." *Journal of Business Logistics* 31, no. 1: 1–21. https://doi.org/10.1002/j.2158-1592.2010.tb00125.x.

Qi, Y., X. Wang, M. Zhang, and Q. Wang. 2023. "Developing Supply Chain Resilience Through Integration: An Empirical Study on an e-Commerce Platform." *Journal of Operations Management* 69, no. 3: 477–496. https://doi.org/10.1002/joom.1226.

Rainer, R. K., Jr., R. G. Richey Jr., and S. Chowdhury. 2025. "How Robotics Is Shaping Digital Logistics and Supply Chain Management: An Ongoing Call for Research." *Journal of Business Logistics* 46, no. 1: e70005. https://doi.org/10.1111/jbl.70005.

Richey, R. G., Jr., S. Chowdhury, B. Davis-Sramek, M. Giannakis, and Y. K. Dwivedi. 2023. "Artificial Intelligence in Logistics and Supply Chain Management: A Primer and Roadmap for Research." *Journal of Business Logistics* 44, no. 4: 532–549. https://doi.org/10.1111/jbl.12364.

Sodhi, M. S., and C. S. Tang. 2021. "Extending AAA Capabilities to Meet PPP Goals in Supply Chains." *Production and Operations Management* 30, no. 3: 625–632. https://doi.org/10.1111/poms.13304.

Srinivasan, R., and M. Swink. 2018. "An Investigation of Visibility and Flexibility as Complements to Supply Chain Analytics: An Organizational Information Processing Theory Perspective." *Production and Operations Management* 27, no. 10: 1849–1867. https://doi.org/10.1111/poms.12746.

Sternberg, H., M. Mathauer, and E. Hofmann. 2023. "Technology Management in Multi-Tier Chains: A Case Study of Agency in Logistics Service Outsourcing." *Journal of Operations Management* 69, no. 4: 536–557. https://doi.org/10.1002/joom.1219.

Sundaresan, S., A. Boysen, and A. Nerkar. 2023. "Adopting Dr. Robot: Responses to Competitor Adoption of Innovation." *Strategic Management Journal* 44, no. 9: 2283–2310. https://doi.org/10.1002/smj.3496.

Teece, D. J., G. Pisano, and A. Shuen. 1997. "Dynamic Capabilities and Strategic Management." *Strategic Management Journal* 18, no. 7: 509–533. https://doi.org/10.1002/(SICI)1097-0266(199708)18:7<509::AID-SMJ882>3.0.CO;2-Z.

Todo, Y., P. Matous, and H. Inoue. 2016. "The Strength of Long Ties and the Weakness of Strong Ties: Knowledge Diffusion Through Supply Chain Networks." *Research Policy* 45, no. 9: 1890–1906. https://doi.org/10.1016/j.respol.2016.06.008.

Tóth, Z., R. Caruana, T. Gruber, and C. Loebbecke. 2022. "The Dawn of the AI Robots: Towards a New Framework of AI Robot Accountability." *Journal of Business Ethics* 178, no. 4: 895–916. https://doi.org/10.1007/s10551-022-05050-z.

Wang, K., B. Huo, M. Tian, and A. C. L. Yeung. 2025. "Revisiting the Interplay of Trust and Contracts: The Roles of Technological Turbulence and Dependence Disadvantage." *Journal of Purchasing and Supply Management* 31, no. 1: 100895. https://doi.org/10.1016/j.pursup.2024.100895.

Wang, L., J. L. Jin, and K. Z. Zhou. 2023. "Technological Capability Strength/Asymmetry and Supply Chain Process Innovation: The Contingent Roles of Institutional Environments." *Research Policy* 52, no. 4: 104724. https://doi.org/10.1016/j.respol.2023.104724.

Wei, S., J. Yin, and W. Chen. 2022. "How Big Data Analytics Use Improves Supply Chain Performance: Considering the Role of Supply Chain and Information System Strategies." *International Journal of Logistics Management* 33, no. 2: 620–643. https://doi.org/10.1108/IJLM-06-2020-0255.

Wieland, A., and C. F. Durach. 2021. "Two Perspectives on Supply Chain Resilience." *Journal of Business Logistics* 42, no. 3: 315–322. https://doi.org/10.1111/jbl.12271.

Xu, Y., F. Jia, L. Wang, and L. Chen. 2024. "Can Digital Transformation Improve Firm Resilience to Supply Chain Disruption? The Role of Diversification Strategies." *Journal of Purchasing and Supply Management* 30, no. 5: 100952. https://doi.org/10.1016/j.pursup.2024.100952.

Zhang, Q., A. Min Du, and B. Lin. 2025. "Driving Total Factor Productivity: The Spillover Effect of Digitalization in the New Energy Supply Chain." *Research in International Business and Finance* 75: 102764. https://doi.org/10.1016/j.ribaf.2025.102764.

Zhang, X., R. Liang, and Y. Chen. 2025. "The Impact of Digital Transformation of Chain-Leading Enterprises on Supply Chain Efficiency." *Supply Chain Management: An International Journal* 30: 369–382. https://doi.org/10.1108/SCM-11-2024-0772.

Zhao, K., Z. Zuo, and J. V. Blackhurst. 2019. "Modelling Supply Chain Adaptation for Disruptions: An Empirically Grounded Complex Adaptive Systems Approach." *Journal of Operations Management* 65, no. 2: 190–212. https://doi.org/10.1002/joom.1009.

Zsidisin, G. A., and S. M. Wagner. 2010. "Do Perceptions Become Reality? The Moderating Role of Supply Chain Resiliency on Disruption Occurrence." *Journal of Business Logistics* 31, no. 2: 1–20. https://doi.org/10.1002/j.2158-1592.2010.tb00140.x.

Supporting Information

Additional supporting information can be found online in the Supporting Information section.