scientific reports

OPEN

The impact of china's artificial intelligence pilot policies on enterprise supply chain resilience

Guangbin Cheng & Hongshuai Zhang

As the "Artificial Intelligence Plus" strategic initiative continues to deepen, the circumstances under which and how artificial intelligence (AI) can enhance the resilience of corporate supply chains are rapidly drawing academic attention. This paper, utilizing data from 4,144 A-share listed companies in China and relevant data from prefecture-level cities spanning from 2016 to 2023 as samples, employs the double machine learning (DML) method with random forest regression as the DML learner to investigate the relationship mechanism between government-level AI policies and corporate supply chain resilience. The results reveal that AI pilot policies can elevate the level of corporate supply chain resilience (with an average increase of 0.0177 units in supply chain resilience in pilot regions, and a 95% confidence interval of [0.0074–0.0281]). This enhancement is primarily achieved by strengthening enterprises' absorptive capacity, resource integration capability, and innovation ability, while the digital foundation and capital investment of regions and enterprises further amplify this positive impact. Meanwhile, the policy's influence exhibits significant heterogeneity, with more pronounced effects in eastern regions, central cities, technology-intensive industries, and state-owned enterprises. When facing external shocks, AI policies can mitigate the adverse impacts caused by such shocks, and this mitigating effect is more significant in the later stages of the shock. Additionally, these policies can drive the improvement of supply chain resilience in non-pilot regions through spatial spillover effects. The conclusions of this study offer practical references for optimizing supply chain management and enhancing supply chain resilience through AI policies, as well as valuable insights for relevant policy formulation and corporate strategic decision-making.

Keywords Artificial intelligence, Supply chain resilience, Absorptive capacity, Resource integration capability, Innovation ability

In the current era, the global economic landscape is undergoing profound and complex transformations, and the global supply - chain system is facing unprecedented risks and challenges. From the perspective of the overall international political and economic situation, influenced by factors such as unilateralism, trade protectionism, and frequent geopolitical conflicts, the development of the global supply chain is showing a fragmented trend. Therefore, how to enhance the risk - resistance capacity of supply chains and improve supply - chain resilience has become a critical issue that global policymakers urgently need to address. In the wave of the global technological revolution, a new generation of information technology centered on artificial intelligence is profoundly reshaping the operational paradigms of the economy and society, providing new opportunities for enhancing supply - chain resilience[1]. As the world's largest developing country and a market for digital technology applications, China is actively promoting the deep integration of new - generation artificial intelligence technology with the real economy. According to the data from the *China Artificial Intelligence Application Development Report (2025)*, innovation and entrepreneurship in the field of artificial intelligence in China have remained active over the past three years, with the number of start - up companies in AI industry applications accounting for 68.2% of the total number of new AI start - up companies. Application investments cover multiple fields such as intelligent vehicles, robots, and intelligent manufacturing. Due to varying degrees of data accumulation and governance across different industries or regions, there are significant differences in the utilization rate, usage patterns, and depth of AI application among enterprises in different vertical fields. Against this backdrop, how to promote the construction of artificial intelligence in a way that suits local conditions and deeply integrate it into all links of the supply system is the core of maintaining market supply - demand stability and building industrial security[2].

Currently, research on artificial intelligence (AI) and supply chain resilience primarily focuses on micro-level aspects such as technology and organization[3,4]. Most researchers quantify the extent of AI application

Shihezi University, Shihezi, Xinjiang, China. email: cgb_jm@shzu.edu.cn

by analyzing the word frequency in annual reports of listed companies, thereby exploring the impact of AI on supply chain resilience at the enterprise level[5]. Although some studies have examined the effects of regional AI development on enterprise supply chain resilience, their research perspectives are confined to the stock status of AI at the macro level[6]. Studies on AI policies have covered various domains, including corporate green innovation, ECG performance, and market competition[7–9]. However, no research has yet delved deeply into the influence of government-level AI policies on enterprise supply chain resilience. Additionally, in terms of model identification strategies, existing literature predominantly employs double fixed-effects models or traditional difference-in-differences models, which are difficult to avoid the limitations imposed by pre-set functional forms[5,9]. Particularly when dealing with high-dimensional data, a large amount of irrelevant or redundant variable information can interfere with the model's identification and analysis of key factors, thereby significantly reducing the accuracy of research conclusions.

Based on this, this paper employs Double Machine Learning (DML), a cutting-edge econometric model, to investigate the policy effects of artificial intelligence (AI) on enterprise supply chain resilience. Compared with the traditional Difference-in-Differences (DID) model, DML offers unique advantages in variable and model selection. From a theoretical perspective, enterprise supply chain resilience is often influenced by numerous factors. However, using high-dimensional control variables for control may lead to the "curse of dimensionality" and multicollinearity issues. In contrast, machine learning, utilizing regularization algorithms, can automatically optimize within a pre-selected set of high-dimensional control variables, thereby obtaining a more precise set of effective control variables. This not only avoids the problem of redundant control variables but also mitigates the endogeneity issues caused by limited control variables, significantly reducing the estimation bias of core parameters due to model misspecification.

Compared with existing research, this paper may make the following marginal contributions: First, it explores the policy effects of artificial intelligence (AI) on supply chain resilience from a macro perspective, enriching the research content on supply chain resilience and providing a new perspective for a deeper understanding of the driving factors of supply chain resilience. Second, based on the dynamic capabilities theory, it constructs a three-dimensional mediating mechanism encompassing absorptive capacity (the proportion of employees with a bachelor's degree or above), resource integration capacity (the logarithm of 365 divided by inventory turnover rate), and innovation capacity (the number of granted patents). This provides a valuable complement to relevant research evaluating the transmission pathways through which AI policies affect enterprise supply chain resilience. Third, grounded in external shocks, it systematically investigates the impact of external risks on supply chain resilience, the chain-stabilizing role of AI policies, and the effects of AI policies on supply chain resilience at different stages of shocks. This holds significant practical implications for enterprises to efficiently respond to environmental changes and prevent supply chain disruptions.

Literature review

The development and popularization of artificial intelligence (AI) have provided a significant opportunity for enhancing supply chain resilience. Currently, relevant research primarily focuses on the following two aspects: Firstly, in terms of measuring supply chain resilience, methodologies include single-indicator measurement and comprehensive-indicator measurement[10,11]. Comprehensive-indicator measurement has emerged as the mainstream approach, with some scholars constructing evaluation index systems based on two dimensions: supply chain resistance capacity and supply chain recovery capacity[11]. Lin et al. further expanded and refined this research framework by incorporating the risk lifecycle theory, constructing a supply chain measurement index system across three stages: adaptation, resistance, and recovery, with a relatively unified measurement approach primarily utilizing the entropy method[12]. Secondly, regarding the exploration of AI's causal effects on supply chains, research perspectives predominantly focus on micro-level impacts, with sample selections including data from listed companies and survey questionnaire data[5,13]. Research content analyzes AI's impact on supply chains from both technological and application layers[14,15]. Currently, only a limited number of scholars have recognized the significance of regional AI development for supply chain resilience, with the primary focus on AI stock levels[6]. Simultaneously, no research has yet conducted a quantitative evaluation of AI policies from a policy perspective. In terms of estimation methods, for studies on AI stock levels, most researchers employ fixed-effects regression models, structural equation models, etc., to conduct relevant explorations[5,16]. Conversely, research on AI policies primarily adopts the difference-in-differences method[17].

In summary, the achievements attained thus far provide substantial theoretical support and empirical evidence for the research content of this paper. However, the following deficiencies remain: Firstly, in terms of causal relationships, although scholars worldwide have recognized the significant impact of artificial intelligence (AI) development on supply chain resilience, there is a notable gap in exploring the policy effects between the two. Particularly in developing countries, some regions face challenges such as weak technological innovation capabilities and inadequate infrastructure levels. Enterprises exhibit insufficient initiative in developing AI and urgently rely on national policy guidance and subsidies to promote AI development. However, no scholars have yet focused on researching the impact of AI policies on supply chain resilience. Secondly, regarding data structure, existing studies predominantly follow a conventional logic of hierarchical matching, where macro-level data is typically used for macro-level analysis, or micro-level data supports micro-level problem research. Only a few scholars have employed cross-level data to explore the impact of AI on supply chain resilience. Cross-level data integrates information such as policy guidance at the macro level and corporate operational data at the micro level, enabling a more comprehensive and three-dimensional representation of AI's impact on supply chain resilience within complex economic systems. However, studies utilizing cross-level data remain scarce in quantity, limiting further in-depth exploration of the relationship between AI and supply chain resilience. Thirdly, concerning identification strategies, most existing research on identifying the policy effects of AI employs the difference-in-differences (DID) method for estimation. However, this method exhibits significant limitations in handling high-dimensional covariates. Traditional DID typically controls for confounding factors through bidirectional fixed effects, but when the number of covariates is large or nonlinear interactions exist, fixed-effects models fail to effectively capture key information, leading to omitted variable bias. In contrast, double machine learning (DML) screens important variables through machine learning algorithms and automatically processes redundant information in high-dimensional data, enabling more accurate identification of policy effects in researching the impact of AI policies on supply chain resilience.

Policy context and theoretical mechanisms

Policy context

The development of artificial intelligence (AI), serving as the "core incubation hub" for the digital and intelligent transformation of industries, functions as a practical carrier for achieving the integrated development of the digital economy and the real economy. On July 20, 2017, the State Council issued the Notice on the Development Plan for the New Generation of Artificial Intelligence, proposing a three-step strategic goal for AI technology. It aims to elevate AI theory, technology, and applications to a world-leading level by 2030. In 2019, the Ministry of Science and Technology issued the Notice on the Work Guidelines for the Construction of National Pilot Zones for the Innovative Development of the New Generation of Artificial Intelligence, officially announcing the launch of pilot projects for these zones in municipalities directly under the central government, sub-provincial cities, and prefecture-level cities. As of April 2024, 18 cities have been approved for the construction of national pilot zones for the innovative development of the new generation of AI. Among them, in 2019, seven cities, namely Beijing, Shanghai, Tianjin, Shenzhen, Hangzhou, Hefei, and Huzhou, were the first to receive approval. In 2020, six cities, including Chongqing, Chengdu, Xi'an, Jinan, Guangzhou, and Wuhan, followed suit. In 2021, five cities, namely Suzhou, Changsha, Zhengzhou, Shenyang, and Harbin, completed the approval process. By this point, a multi-tiered and multi-regional collaborative development pattern for the layout of pilot cities in the experimental zones has initially taken shape.

Based on the strategic deployment of the national pilot zones for innovative development of the new generation of artificial intelligence, each pilot city, taking into account its unique regional endowments, actively promotes the intelligent upgrading of enterprise supply chain systems. In terms of intelligent production, the focus is on facilitating the intelligent reconstruction of production lines. Enterprises are encouraged and guided to establish factory big data systems to achieve networked and intelligent development in production and management. Regarding smart logistics, pilot cities strengthen the research, development, and widespread application of intelligent logistics equipment, enhancing the level and efficiency of warehouse operation and management. Simultaneously, they further refine logistics information platforms and intelligent cargo distribution and scheduling systems. By reducing human intervention in the production process and improving logistics operational efficiency through these two approaches, supply chain systems can swiftly adjust and respond flexibly when faced with external shocks, thereby enhancing their resilience. Therefore, with the extensive application of artificial intelligence in supply chains driven by policies, exploring the impact of AI policies on supply chain resilience holds significant theoretical and practical implications. Moreover, the "New Generation AI Innovation" pilot policy, as a quasi-natural experiment, provides effective support for this study.

Theoretical mechanisms

AI policies have propelled the widespread application of relevant technologies in supply systems, significantly enhancing the resistance, adaptability, and resilience of supply chains while improving their response speed, thereby systematically elevating the overall resilience level of supply chains[18]. Firstly, in terms of risk resistance, AI, relying on its powerful data processing and analysis capabilities, can keenly perceive market dynamics and potential risks, and issue early warnings in advance, providing enterprises with sufficient time to formulate response strategies and effectively reducing the risk of supply chain "disruptions" caused by uncertain shocks[6]. Secondly, regarding adaptability, by leveraging industrial internet platforms, it is possible to accurately capture market dynamic information and rapidly generate procurement plans, production schedules, and logistics scheduling solutions based on market demands, enabling the supply chain system to align more flexibly and efficiently with changes in market demand[19]. In terms of resilience, AI, relying on digital twin systems, simulates supply chain disruption scenarios and generates optimal recovery paths, which not only significantly reduces the trial-and-error costs for enterprises but also ensures that enterprises can swiftly and precisely adjust resource allocation when supply chains are disrupted, enhancing their ability to recover from disruptions[20]. It is evident that AI has a significant direct effect on enhancing the resilience of enterprise supply chains, providing solid technological support for enterprises to cope with complex and ever-changing market environments.

Based on the above analysis, this paper proposes the following hypotheses:

H1: Artificial intelligence policies can enhance the level of enterprise supply chain resilience.

Dynamic capabilities refer to the ability of enterprises to possess innovative traits, perceive changes in the external environment, and adjust resource allocation accordingly to effectively respond to external changes. This capability can be further divided into three dimensions: absorptive capacity, resource integration capacity, and innovation capacity[21]. In the supply network, as a node, an enterprise's dynamic adjustment ability to cope with external shocks is the core factor determining supply chain resilience. Based on this, this paper constructs a mechanism for the impact of artificial intelligence on supply chain resilience based on the dynamic capabilities theory. And according to the research content, the three dimensions of dynamic capabilities are defined from the following three aspects: Absorptive capacity refers to the ability of enterprises to rely on digital technologies and integrate high-quality talents to identify market dynamics, absorb them, and apply them commercially[22]. Resource integration capacity refers to the ability to achieve resource sharing and dynamic allocation through intelligent collaboration platforms, ensuring stable operations in complex and ever-changing market environments[23]. Innovation capacity refers to the ability of enterprises to leverage massive data to gain insights into market trends and potential demands, accelerate product iteration, and drive business model innovation, thereby maintaining their core competitiveness[24].

1. Absorptive Capacity.

Based on the theory of absorptive capacity, an enterprise's absorptive capacity encompasses comprehensive abilities such as knowledge acquisition and utilization. Artificial intelligence (AI) policies have played a favorable auxiliary role in enhancing absorptive capacity. Firstly, during the implementation of AI policies, the widespread application of digital technologies has broken through the temporal, spatial limitations, and channel barriers of traditional knowledge acquisition. With this technological advantage, enterprises can grasp interdisciplinary and cross-field cutting-edge knowledge and technological trends in real-time, precisely, and comprehensively, thereby expanding their knowledge horizons and thinking boundaries[25]. Secondly, driven by AI policies, AI algorithms such as machine learning, with their powerful data processing and analysis capabilities, can deeply analyze knowledge such as market dynamics and industry development trends, and establish an intrinsic connection with enterprise resources. They can deeply explore the convergence points in the following text) between the two, accelerating the efficient transformation of knowledge from a theoretical form into practical productivity and its full utilization[26]. The strengthening of an enterprise's absorptive capacity also creates favorable conditions for enhancing supply chain resilience. On the one hand, by leveraging enhanced absorptive capacity, enterprises can transform complex market and technological trends into core content for their internal knowledge bases, helping them accurately identify potential risks, optimize the layout of their supply chain structures in advance, and enhance the supply chain's resistance while empowering the improvement of the enterprise's supply chain resilience level[27]. On the other hand, with strong absorptive capacity, enterprises can promptly adjust production, procurement, logistics, and other aspects when facing emergencies, enabling the supply chain to maintain stable operation and sustainable development in complex environments, thereby enhancing supply chain resilience[28]. Therefore, this paper argues that AI policies can enhance enterprise supply chain resilience by strengthening enterprises' absorptive capacity.

2. Resource Integration Capability.

According to resource dependence theory, the core of resource integration capability lies in the ability to transcend one's own resource limitations and efficiently connect with external resources. Artificial intelligence (AI) policies serve as a bridge for enterprises to access scarce resources, resolving the challenge of resource acquisition and thereby promoting the enhancement of enterprise resource integration capability. On one hand, the establishment of the Internet of Things (IoT) and data-sharing platforms during the implementation of AI policies can swiftly integrate vast amounts of internal and external enterprise data, break down information barriers between departments, achieve seamless integration and efficient communication among different departments, and significantly enhance the enterprise's information integration capability[29]. On the other hand, intelligent algorithms can intelligently schedule resources based on key factors such as changes in market demand, supply disruption risks, and logistics delivery times, thereby improving the enterprise's material resource integration capability[30]. The strengthening of enterprise resource integration capability provides resource support for enhancing supply chain resilience. Firstly, the enhancement of resource integration capability can effectively address issues such as the bullwhip effect of demand amplification in the supply chain system, ensuring that the production and supply schedules of node enterprises remain synchronized and reducing the risk of supply chain disruption[31]. Secondly, resource integration capability reflects the strength of an enterprise's flexibility and adaptability; a stronger resource integration capability implies that the enterprise can rapidly respond to market changes and external shocks. When there are fluctuations in demand or supply disruptions in the market, various entities can swiftly coordinate actions to integrate resources across organizations, constructing a more risk-resistant supply chain system[32]. Therefore, this paper argues that AI policies can enhance supply chain resilience by strengthening enterprise resource integration capability.

3. Innovation Capability.

According to the innovation system theory, innovation is the result of the collaborative efforts of multiple individuals, and policies serve as a crucial link in optimizing the structure of the innovation system. Therefore, artificial intelligence (AI) policies hold significant importance in promoting corporate innovation capabilities. Firstly, during the implementation of AI policies, relevant technologies are deeply embedded, enabling enterprises to integrate real-time market demand evolution, technological development trends, and industry competitive intelligence, forming an intelligent decision-making system that encompasses multi-dimensional information. This aids enterprises in clarifying their innovation directions and reducing innovation risks[24]. Secondly, AI policy pilot programs act as innovation incubators, promoting collaboration between enterprises and industry-university-research institutions, fostering an innovation ecosystem characterized by multi-agent interaction and the free flow of various innovation elements[33]. The strengthening of innovation capabilities also provides a core driving force for the resilience of corporate supply chains. On one hand, innovation-driven differentiated product development strategies can precisely match diverse market demands, endowing supply chains with stronger dynamic demand adaptability[34]; on the other hand, the integration of innovation elements throughout the entire supply chain process, including production, logistics, and sales, enhances the operational efficiency and stability of supply chain entities and structures[35]. Therefore, this paper argues that AI policies can enhance corporate supply chain resilience by strengthening corporate innovation capabilities.

Based on the aforementioned analysis, this study proposes the following hypothesis::

H2: Artificial intelligence (AI) policies can strengthen corporate dynamic capabilities, thereby promoting the enhancement of corporate supply chain resilience.

In the operation of supply chain systems, the degree of digitization and the level of capital investment, serving as the foundation and guarantee for the application and research and development (R&D) of artificial intelligence (AI), play a pivotal role in promoting the enhancement of corporate supply chain resilience through AI policies[36]. From the perspective of digitization, regional digital economies leverage their technological advantages to establish efficient and convenient channels for the full interaction of supply and demand information. Supply chain nodes can rapidly adjust production plans based on precise data, efficiently respond to market fluctuations and unexpected risks, and provide underlying support for risk anticipation in the supply chain system[37]. The digital transformation of enterprises provides a technological foundation for AI applications, eliminating the barriers to adapting AI to supply chain scenarios through unified data structures and standardized business processes, thereby significantly improving the sensitivity and response speed of machine learning algorithms to interruption signals[38]. Regarding capital investment, policies such as financial subsidies and tax incentives from regional governments accelerate the integrated development of AI and supply chain systems. The widespread application of AI technology promotes collaborative cooperation among supply chain entities, enhances the risk resistance capability of supply chains, and strengthens the application space of AI in enhancing supply chain resilience[39]. R&D investment in the AI field by enterprises reflects their innovative capacity and growth potential, effectively shortening product production cycles, improving production efficiency, accelerating inventory turnover, and reducing idle corporate resources, which is conducive to enhancing the coordination and risk response capabilities of various supply chain links[40]. The action mechanism diagram of how AI policies affect the resilience of enterprise supply chains is shown in Fig. 1.

Based on the aforementioned analysis, this paper proposes the following hypothesis:

H3: The digitization and capital investment at both regional and corporate levels exert a positive moderating effect on the enhancement of corporate supply chain resilience enabled by artificial intelligence (AI) policies.

Research design

Indicator construction

Dependent variable

The dependent variable is supply chain resilience (denoted as *Sup*). Based on an integration of existing research, this study posits that supply chain resilience should encompass three capabilities: the resistance capacity during the initial phase of shocks, the dynamic adjustment capacity during sustained shock phases, and the reconstruction capacity after supply chain disruptions. This framework deconstructs the resilience level of supply chain systems from dual perspectives of temporal sequence and capability dimensions, aligning with the lifecycle patterns of supply chain risk evolution while precisely identifying stage-specific weaknesses in resilience construction. It thereby provides actionable pathways for enhancing supply chain resilience under the new development paradigm. Consequently, the indicator measurement system evaluates resilience through three dimensions: resistance capacity, adaptive capacity, and recovery capacity of supply chains.

First, supply chain resistance capacity primarily reflects the ability of supply chains to maintain basic operations through firms' internal preventive mechanisms prior to shock occurrences. Drawing on the research of Lu, Y. et al. (2025), this study measures firms' supply resistance capacity by dividing the number of a firm's top five stable clients by five[41]. The number of the top five stable customers reflects a company's customer stability and market foundation in the market. Enterprises with a relatively large number of stable customers generally imply that their products or services possess strong market competitiveness, enabling them to withstand fluctuations in market demand to a certain extent. Intuitively, it can be inferred that when facing external shocks, such

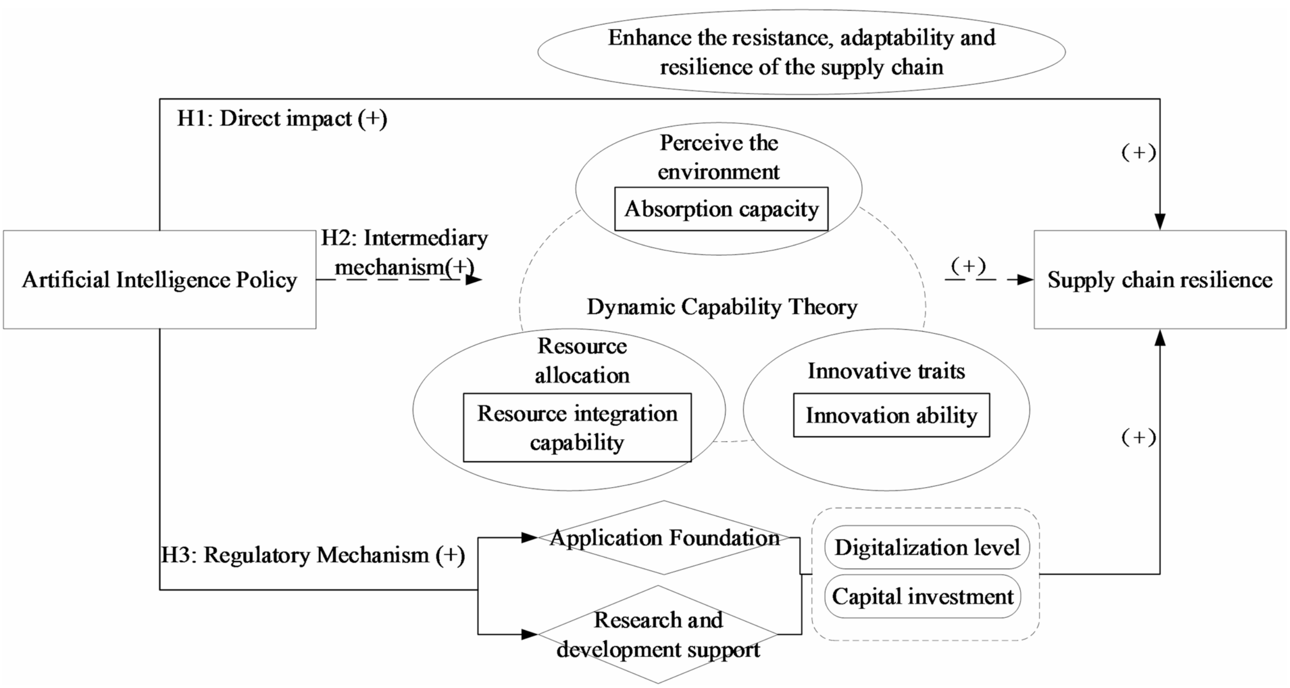

Fig. 1. Theoretical Mechanism Diagram of AI-Driven Enhancement of Supply Chain Resilience.

enterprises have a stronger ability to maintain operations by relying on stable customer relationships, that is, the stronger the supply chain resistance. The calculation formula for supply chain resistance is as follows:

$$Res_{it}=\sum_{j=1}^{5}F_{i,t}(i,c_j)/5 \tag{1}$$

$$F_{i,t}(i,c_j)=f_{i,t}(i,c_j)\times f_{i,t-1}(i,c_j) \tag{2}$$

In Eq. (1),Res_{it} represents the supply chain resistance capacity. If $F_{i,t}(i,c_i)$= 1, it indicates that there exists a stable supply relationship between enterprise *i* and customer c_j; otherwise, no such relationship exists. In Eq. (2), $f_{i,t}(i,c_j)$and$f_{i,t-1}(i,c_j)$ respectively denote whether there is a stable supply relationship between enterprise *i* and customer $c_j$in year *t* and year $t-1$ A value of 1 indicates the presence of such a relationship, while a value of 0 indicates its absence.

Second, supply chain adaptability manifests as the agility to dynamically adjust strategies in response to environmental disruptions. Following the methodology of Zhang, Y. D. et al. (2025), this capacity is quantified through the supply-demand deviation index (SDDI)[42]. The lower the deviation degree, the more precise means the supply chain can employ to narrow the gap between supply and demand, indicating a stronger adaptability of the supply chain. The supply-demand deviation degree reflects whether the actual production of the supply chain can more accurately align with market demand. In practical operations, if enterprises can promptly adjust their production rhythms and inventory strategies in response to real-time changes in market demand, ensuring a high degree of consistency between product supply and market demand, they can more effectively avoid inventory overstocking or stockouts when facing external shocks. This intuitively reflects that the enterprises possess strong capabilities to adapt to environmental changes. Therefore, the supply-demand deviation degree is used to measure the adaptability of the supply chain, and its specific definition is as follows:

$$Adaptability_{it}=\frac{\sigma(Production_{it})}{\sigma(Demand_{it})}-1 \tag{3}$$

$$Production_{it}=Cost_{it}+Inv_{it}-Inv_{it-1} \tag{4}$$

In Eq. (3),$Adaptability$ represents the supply - demand deviation degree, $\sigma(\cdot)$denotes the variance of variables. The numerator and denominator respectively indicate the volatility of enterprise production and demand. $Production$ and $Demand$ signify the enterprise production volume and demand volume, respectively. The enterprise production volume is calculated using Eq. (4), where $Cost$ is the operating cost of the enterprise, Inv represents the net value of the enterprise's inventory at the end of the year, and the enterprise demand volume takes the enterprise cost (denoted as $Cost$) as a proxy variable.

Third, supply chain recovery capability primarily reflects the efficiency of restoring normal operations through resource reconfiguration and emergency mechanisms following disruptions. Following the methodology of Qi, R. J. et al. (2024), this capability is measured by estimating the residuals of firm performance[11]. Enterprise performance reflects a company's profitability. External shocks can have a detrimental impact on a company's profitability. By estimating the fluctuation range (residual) of the actual value of enterprise performance deviating from the expected value, the residual can reflect a company's dynamic response capability to restore normal operational status through mobilizing redundant resources and making strategic adjustments after a supply - chain disruption. The specific calculation method is as follows:

$$Performance_{it}=\alpha_0+\alpha_1 Size_{it}+\alpha_2 Age_{it}+\alpha Lev_{it}+\alpha_4 Board_{it}+\alpha_5 Indpe_{it}+\sigma_i+\sigma_t+\varepsilon_{it} \tag{5}$$

In Eq. (5), variable $performance_{it}$ represents firm performance, which is measured by the ratio of total profit to the number of employees. The remaining variables are a series of control variables related to firm performance, including firm size (*Size*), firm age (*Age*), leverage ratio (*Lev*), board size (*Sca*), and the proportion of independent directors (*Man*). $\sigma_i$and σ_t denote firm - fixed effects and time - fixed effects, respectively. The residual values estimated using the above formula represent the recovery capacity of the supply chain. A larger value indicates stronger recovery capacity, while a smaller value implies weaker recovery capacity.

Based on the aforementioned indicators, a comprehensive indicator evaluation system is constructed. In terms of selecting the measurement method, this paper draws on existing research by calculating the mean of the correlation coefficients between variables for judgment. First, the supply chain resilience index is calculated using the entropy method, principal component analysis, and equal - weight method respectively according to the above - mentioned indicator evaluation system. Then, the Spearman correlation coefficients among the three methods are computed. Finally, the average value of the correlation coefficients between one method and the other two methods is calculated. A higher average value indicates a higher consistency between that method and the other methods, and thus a more reasonable conclusion. As shown in Supplementary Table 2, the entropy method has the highest mean of correlation coefficients with principal component analysis and the equal - weight method. Therefore, the entropy method is ultimately selected to measure supply chain resilience[43]. By calculating the correlation coefficients between supply - chain resilience and its sub - variables and creating a graph (see Supplementary Fig. 1), it can be observed that the sub - variables are all significantly correlated with supply - chain resilience, and the signs are consistent with expectations, which reflects the rationality of the indicator construction.

Core explanatory variable

Artificial Intelligence (AI). It is measured using the pilot projects of "Next - Generation Artificial Intelligence Innovation". From the time when the Ministry of Science and Technology announced the first batch of pilot policies for "National Next - Generation Artificial Intelligence Innovation", it can be inferred that the AI policy commenced in 2019. In this paper, enterprises located in cities where the headquarters of listed companies are situated and that are approved for the "National Next - Generation Artificial Intelligence Innovation" pilot projects in the current year or subsequent years are assigned a value of 1, while others are assigned a value of 0. To ensure the accuracy and completeness of the estimated policy effects, this paper examines the expected benefits and spatial spillover effects in the empirical section.

Control variables

To enhance the accuracy and reliability of the study, the following control variables are incorporated: (1)Return on Assets (*Rep*), measured as the ratio of net profit to the average balance of total assets; （2） Firm Size (*Size*), measured as the natural logarithm of total assets; （3）Leverage Ratio (*Lev*), measured as the ratio of total liabilities to total assets; （4）Firm Age (*Age*), measured as the logarithm of the （5） Board Size (*Sca*), measured as the number of board members plus one; （6） Proportion of Independent Directors (*Man*), measured as the ratio of independent directors to total board members; （7）Firm Value (*Tob-Q)*, measured using Tobin's Q; （8） Fixed Asset Ratio (*FA*), measured as the ratio of fixed assets to total assets; （9）Ownership Concentration (*Sto*), measured as the shareholding ratio of the largest shareholder.

Model construction

To accurately identify the causal relationship between artificial intelligence (AI) and the resilience of corporate supply chains, the pilot projects of "National Next - Generation Artificial Intelligence Innovation" are employed as a proxy variable for AI. The Double/Debiased Machine Learning (DML) approach is utilized for empirical assessment, and the Random Forest algorithm is adopted for estimation through 5 - fold cross-validation. Following the approach of Wen, H. W. et al. (2024)[44], we construct a Double Machine Learning (DML) model within a semi-parametric causal inference framework to identify the effects of pilot policies. The model is structured as follows:

$$Sup_{it} = \theta_0 AI_{it} + g(X_{it}) + U_{it} \tag{6}$$

$$E(U_{it}|AI_{it}, X_{it}) = 0 \tag{7}$$

$$AI_{it} = k_0(X_{it}) + M_{it} \tag{8}$$

$$E(M_{it}|X_{it}) = 0 \tag{9}$$

In Eq. (6), Suprepresents the dependent variable, denoting supply chain resilience; *i* denotes the city; *t* denotes the year; AI is the treatment variable representing the "National New Generation Artificial Intelligence Innovation" pilot policy, where AI=1 if city *i* implements the pilot policy in year *t* or later, and AI=0 otherwise. θ_{it} quantifies the policy effect of the "National New Generation Artificial Intelligence Innovation" pilot policy on supply chain resilience. X_{it}represents a high-dimensional set of control variables with an unknown functional form, which requires estimation via machine learning algorithms. U_{it} is the error term satisfying the zero-mean assumption. To mitigate regularization bias in Eqs. (6) and (7), auxiliary regressions are constructed as shown in Eqs. (8) and (9). First, machine learning algorithms are applied to estimate the auxiliary regressions and obtain their residuals $\hat{M}_{it} = AI_{it} - \hat{m}(X_{it})$. Second, the regression function $k_0(X_{it})$ of the treatment variable on high-dimensional control variables is estimated, yielding the specific form $\hat{k}_o(X_{it})$, which is substituted into the transformed Eq. (6) $Sup_{it} - \hat{g}(X_{it}) = \theta_0 AI_{it} + U_{it}$. Finally, $\hat{M}(X_{it})$ is used as an instrumental variable for AI_{it} in regression, producing an unbiased estimator $\hat{\theta}_0$

$$\hat{\theta} = (\frac{1}{n}\sum_i \hat{M}_{it} AI_{it})^{-1} \frac{1}{n}\sum_i \hat{M}_{it}(Sup_{it} - \hat{g}(X_{it})) \tag{10}$$

Data sources

This paper selects Chinese A - share listed companies from 2016 to 2023 as the research sample. The company - level data mainly come from the CSMAR Database and the Wind Database, while the provincial and prefecture - level city data are sourced from the China Statistical Yearbook and the China City Statistical Yearbook. First, data of ST, ST* - type enterprises, and financial enterprises are excluded. Second, the paper deals with missing values. If any variable used for analysis has a missing value, the corresponding sample will be excluded from the entire analysis (the exclusion steps are shown in Supplementary Fig. 2). After the above data processing, 22,188 observations are finally obtained. The descriptive statistical results of the main variables are presented in Table 1.

Empirical findings and analysis

Benchmark regression results and analysis

Equations (6)–(10) are employed to estimate the policy effects of artificial intelligence (AI) on the resilience of corporate supply chains, with the benchmark regression results presented in Table 2. Column (1) only controls for the linear terms of the control variables. Column (2) further controls for the quadratic terms on the basis of Column (1). It can be observed that the estimated coefficient of AI is significantly positive at the 1% level, indicating that an increase in the level of urban AI can enhance the resilience of enterprise supply

Variables	Measurement method	Unit	Observes	Mean	SD	Min	Max
Sup	It was measured by the entropy method	—	22,188	0.7219	0.3106	0.0000	0.9995
Res	The number of stable customers of the top five clients/5	—	22,188	0.5168	0.4779	0.0000	1.0000
Adaptability	It is calculated based on formulas (3)–(4)	—	22,188	−0.0167	0.1728	−0.5071	0.8804
Performance	It is estimated based on Formula (5)	Ten thousand yuan per person	22,188	−0.4437	32.5679	−110.7056	166.4966
AI	It is collated from relevant policy documents of the Ministry of Science and Technology	—	22,188	0.3454	0.4755	0.0000	1.0000
Rep	The average balance of the enterprise's net profit divided by total assets	%	22,188	0.0080	0.0246	−1.2823	2.3044
Size	Ln(Total Assets of the Enterprise)	—	22,188	23.8912	1.3763	19.4612	30.2666
Lev	The ratio of total liabilities to total assets of an enterprise	%	22,188	0.4109	0.3354	0.0144	39.0110
Age	Take the logarithm of the sample examination year minus the enterprise registration year	—	22,188	2.9647	0.3174	1.0986	4.8122
Sca	The number of board members increases by 1	people	22,188	2.2197	0.1740	0.0000	2.9444
Man	Number of independent directors/number of board members	%	22,188	0.3360	0.0457	0.0000	0.6667
Tob-Q	Tobin Q	%	22,188	2.0928	5.1518	0.6121	719.7570
FA	Enterprise fixed assets/total assets	%	22,188	0.0403	0.0315	0.0000	0.3673
Sto	The shareholding ratio of the largest shareholder	%	22,188	33.2135	14.9154	1.8400	89.9900

Table 1. Descriptive statistics of key Variables.

Variables	(1)	(2)	(3)	(4)
AI	0.0126***	0.0120***	0.0177***	0.0177***
	(0.0041)	(0.0041)	(0.0053)	(0.0053)
95%CI	[0.0046,0.0207]	[0.0039,0.0200]	[0.0073,0.0280]	[0.0074,0.0281]
Margin	0.0116***	0.0118***	0.0120***	0.0121***
	(0.0022)	(0.0022)	(0.0024)	(0.0024)
Control	Yes	Yes	Yes	Yes
Control^2	N0	Yes	N0	Yes
Fixed effect	N0	N0	Yes	Yes
N	22,188	22,188	22,188	22,188

Table 2. Benchmark regression Results. Note: ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The values in parentheses are robust standard errors. Fixed effects refer to year, city, and firm fixed effects. The same applies below.

chains, which initially verifies Hypothesis H1 in this paper. Columns (3) and (4) incorporate fixed effects on the basis of Columns (1) and (2) respectively. It can be seen that while the magnitudes of the estimated coefficients change, their signs and significance remain consistent. In terms of economic significance, the full-variable regression coefficient is 0.0177, suggesting that for every 1% increase in the standard deviation of AI, the level of supply chain resilience will increase by 1.1659% relative to its mean(Calculation formula: Coefficient of the explanatory variable × standard deviation of the explanatory variable ÷ mean of the explained variable *100%). The Margin column lists the marginal effect of AI as 0.0121, indicating that after the implementation of the national new-generation AI innovation policy in the prefecture-level city where the enterprise is located, the supply chain resilience increases by an average of 0.0121 units compared to areas without the pilot policy. Artificial intelligence (AI) policies provide guidance and support for enterprises in applying AI technologies, reducing the costs and risks associated with acquiring and utilizing these technologies and enhancing the level of AI application among enterprises. This enables enterprises to respond more flexibly and efficiently to various uncertain factors in the supply chain, significantly strengthening the resilience of corporate supply chains. To mitigate the confounding effect of enterprises' expectations of obtaining AI innovation pilot status on the policy treatment effect, interaction terms between "whether a city is a National Next - Generation AI Innovation Pilot City" and "the period prior to the pilot recognition, two periods prior, and three periods prior" are included in the regression. The results (see Appendix Table 4) indicate that the coefficients of the interaction terms are all insignificant, suggesting that there is no significant anticipation effect before the recognition process.

Endogeneity tests

Considering the potential bidirectional causality between artificial intelligence (AI) and corporate supply chain resilience, although control variables have been selected from multiple perspectives, omitted variable bias may still lead to endogeneity issues. Therefore, instrumental variables (IVs) are selected for testing based on a double machine learning model. First, following Guo, C. Y. et al. (2025), the instrumental variable (IV1) is constructed by multiplying the reciprocal of the shortest distance between the firm and the nearest port with the proportion of AI-related terms in the firm's vocabulary[45]. Firms closer to ports incur lower logistics costs and shorter transportation times, enabling faster material allocation and operational recovery during external shocks, thus satisfying the relevance condition. Additionally, the geographical distance between a firm's city and the nearest port is a long-term characteristic largely unaffected by the firm's current AI adoption decisions, remaining invariant to whether or how extensively the firm adopts AI, thereby meeting the exogeneity condition. Second, the lagged dependent variable is used as an alternative instrumental variable (IV2). The IV regression results, as shown in Table 3, demonstrate that the coefficients of AI are positive under both IV specifications, with statistical significance at the 10% and 1% levels, respectively. This indicates that after addressing endogeneity concerns, AI continues to significantly enhance corporate supply chain resilience.

Robustness tests

Replace the dependent variable

To avoid the issue of the contingency of conclusions caused by a single measurement approach, robustness tests are conducted from two aspects: changing measurement indicators and measurement methods. At the level of changing measurement indicators, on the one hand, referring to the research of Chen et al., enterprise supply - chain resilience is re - measured from two dimensions: supply - chain resistance capacity and supply - chain recovery capacity[46]. On the other hand, following the practice of Zheng et al., the natural logarithm of the ratio of accounts receivable to revenue is used to measure supply - chain resilience. This indicator is a reverse indicator, where a lower value indicates stronger supply - chain resilience[10]. At the level of changing measurement methods, the equal - weight method and factor analysis method are respectively used for re - measurement, and regression tests are conducted again. As shown in columns (1)–(4) of Table 4, after replacing different types of explained variables, artificial intelligence can still significantly promote the improvement of supply - chain resilience, which proves the robustness of the core conclusions in this paper.

Changing the Estimation method

Given that the main effect is estimated using the Double Machine Learning approach, to circumvent potential endogeneity treatment bias or other underlying limitations inherent in this method and thereby ensure the accuracy and reliability of the estimation results, in the robustness test section of this study, the research method is replaced with the Difference - in - Differences (DID) method and the Propensity Score Matching - based Difference - in - Differences (PSM - DID) method for analysis. When conducting PSM, this paper selects all control variables as covariates and performs 1:1 nearest - neighbor matching without replacement. The estimation results of DID and PSM - DID are presented in columns (5) and (6) of Table 4. The coefficients of AI are all significant at the 1% level, which further demonstrates the reliability of the conclusions.

Exclude municipalities directly under the central government

Given that the unique characteristics of municipalities directly under the central government may introduce certain interference into the estimation results, we exclude the four municipalities—Beijing, Tianjin, Shanghai, and Chongqing—from the sample. The results, as shown in Column (7) of Table 4, indicate that the estimated coefficient is 0.0170 and statistically significant at the 1% level. This suggests that after excluding these special samples, artificial intelligence continues to enhance corporate supply chain resilience, thereby reaffirming the robustness of our core findings.

Exclude the impacts of the COVID-19 pandemic

Exogenous shocks, such as supply-demand fluctuations, logistics disruptions, and policy interferences caused by the COVID-19 pandemic, may distort the normal operational mechanisms of corporate supply chains. Therefore, this study further excludes research samples post-2019 and conducts a re-examination. The results, as shown in Column (8) of Table 4, indicate that the estimated coefficient is significantly positive, thereby reaffirming the robustness of our findings.

	(1)	(2)
Variables	**IV1**	**IV2**
AI	0.4075***	32.0164***
	(0.0254)	(10.9152)
95%CI	[0.3577,0.4574]	[10.6231,53.4098]
Control	Yes	Yes
Control^2	Yes	Yes
Fixed effect	Yes	Yes
N	22,188	17,951

Table 3. Endogeneity Test. Note: As IV2 employs the lagged one-period explained variable as an instrumental variable, it will result in the loss of one-period samples, leading to a reduction in the total sample size.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Replace the explained variable				**Change the estimation method**		**Eliminate outliers**			
Variables	**Change the measurement indicators**	**Single indicator**	**Equal weight**	**PCA**	**DID**	**PSM—DID**	**Delete municipalities directly under the Central Government**	**Excluding the impact of the epidemic**	**Tail reduction by 1%**	**Tail reduction by 5%**
AI	0.0251***	−3.2728**	0.0062**	0.0116*	0.0153***	0.0132***	0.0170***	0.0481***	0.0182***	0.0159***
	(0.0074)	(1.5135)	(0.0029)	(0.0067)	(0.0029)	(0.0033)	(0.0054)	(0.0084)	(0.0053)	(0.0052)
95%CI	[0.0106,0.0395]	[−6.2391, −0.3065]	[0.0006,0.0118]	[−0.0015,0.0247]	[0.0097,0021]	[0.0067,0.0198]	[0.0063,0.0276]	[0.0317,0.0645]	[0.0079,0.0285]	[0.0057,0.0261]
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$Control^2$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	22,188	22,188	22,188	22,188	22,188	17,835	17,340	8,582	22,188	22,188

Table 4. Robustness tests.

Variables	(1)	(2)	(3)	(4)
AI	0.0161***	0.0265***	0.0225***	0.0305***
	(0.0044)	(0.0047)	(0.0044)	(0.0047)
95%CI	[0.0075,0.0247]	[0.0174,0.0357]	[0.0140,0.0311]	[0.0213,0.0398]
Smart City	Yes	No	No	Yes
Innovative City	No	Yes	No	Yes
Free Trade Zone	No	No	Yes	Yes
Control	Yes	Yes	Yes	Yes
$Control^2$	Yes	Yes	Yes	Yes
Fixed effect	Yes	Yes	Yes	Yes
N	22,188	22,188	22,188	22,188

Table 5. Excluding the impacts of other Policies.

	(1)	(2)	(3)	(4)	(5)
Variables	1:2	1:7	Ridge	Gradient boosting	Neural network
AI	0.0149***	0.0163***	0.2682**	0.0224***	0.5789***
	(0.0053)	(0.0053)	(0.1111)	(0.0055)	(0.0053)
95%CI	[0.0045,0.0254]	[0.0060,0.0266]	[0.0504,0.4861]	[0.0116,0.0332]	[0.5685,0.5892]
Control	Yes	Yes	Yes	Yes	Yes
$Control^2$	Yes	Yes	Yes	Yes	Yes
Fixed effect	Yes	Yes	Yes	Yes	Yes
N	22,188	22,188	22,188	22,188	22,188

Table 6. Reconfiguration of machine learning Models.

Winsorization test
To mitigate the influence of outliers on estimation results, we applied 1% and 5% bilateral Winsorization to all continuous variables in this study before incorporating them into the regression equations. The results, presented in Columns (9) and (10) of Table 4, reveal that the coefficient for artificial intelligence is significantly positive, thereby reaffirming the robustness of our core findings.

Excluding the impacts of other policies
During the sample period, in addition to the national innovation pilot program for the new generation of artificial intelligence, other policy instruments, such as the development of smart cities, innovative cities, and free trade zones, were also implemented. To exclude the interference of these policies on the regression results, this study incorporates the three policy types separately into the regression models, as shown in Columns (1)–(3) of Table 5, and simultaneously controls for all three policy types, as presented in Column (4) of Table 5. The results indicate that, under the premise of excluding interference from other policies, the estimated coefficient of artificial intelligence remains significantly positive, thereby reaffirming the robustness of the core conclusions in this paper.

Resetting the machine learning model
To mitigate the impact of specification bias in double machine learning models on research conclusions, robustness tests were conducted from two perspectives: resetting the sample splitting ratio and altering machine learning algorithms. First, the sample splitting ratio was adjusted from the benchmark ratio of 1:4 to 1:2 and 1:7, with results presented in Columns (1) and (2) of Table 6. Second, the machine learning model was reconfigured from the benchmark random forest algorithm to ridge regression, gradient boosting, and neural network algorithms, with results shown in Columns (3)-(5) of Table 6. It is evident that under both approaches, the impact of artificial intelligence on firm supply chain resilience remains consistent in terms of direction and statistical significance, except for variations in coefficient magnitudes. This reaffirms the robustness of the study's core conclusions.

Benchmark regression results and analysis
The preceding sections have validated that artificial intelligence (AI) policies can effectively enhance the level of corporate supply chain resilience. The following section will focus on verifying the mechanism through which AI policies influence corporate supply chain resilience. Based on the theoretical analysis in the preceding sections, a mechanism research framework is constructed from three aspects: absorptive capacity, resource integration capacity, and innovation capacity. Empirical tests are conducted by constructing the following testing models:

$$M_{it} = \beta_0 + \beta_1 AI_{it} + \beta_2 X_{it} + \sigma_i + \sigma_j + \sigma_t + \varepsilon_{it} \tag{11}$$

$$Sup_{it} = \lambda_0 + \lambda_1 M_{it} + \lambda_2 X_{it} + \sigma_i + \sigma_j + \sigma_t + \varepsilon_{it} \quad (12)$$

$$Sup_{it} = \gamma_0 + \gamma_1 AI_{it} + \gamma_2 M_{it} + \gamma_3 X_{it} + \sigma_i + \sigma_j + \sigma_t + \varepsilon_{it} \quad (13)$$

In Eqs. (11)–(12),M_{it} represents the mechanism variable, X_{it}denotes the set of control variables, and all other variables remain consistent with those in Eq. (6).

Absorption capacity
This study aims to verify whether artificial intelligence (AI) policies can promote the enhancement of corporate supply chain resilience by improving absorptive capacity. The proportion of employees with a bachelor's degree or above in a company is used to measure absorptive capacity. Employees with higher educational levels generally possess stronger logical analysis skills, information - processing capabilities, and interdisciplinary knowledge - integration abilities. A higher proportion indicates that the company has a denser network of knowledge - absorption nodes and stronger capabilities for absorbing and transforming external information. As shown in the results of columns (1) and (2) of Table 7, the regression coefficients of AI policies on absorptive capacity and of absorptive capacity on supply chain resilience are 0.5062 and 0.0009, respectively, and both have passed the significance tests at the 1% and 5% levels. In column (3), after simultaneously introducing AI and absorptive capacity, the regression coefficients of both on supply chain resilience remain significantly positive, indicating that AI policies can enhance supply chain resilience by improving a company's absorptive capacity. After the implementation of AI policies, digital technologies and intelligent algorithms have been widely applied, enabling companies to break through the limitations of traditional knowledge acquisition while accelerating the transformation and utilization of knowledge, thereby effectively improving their absorptive capacity. The strengthening of a company's absorptive capacity enhances its ability to identify potential supply - chain risks and respond to them, thus contributing to the improvement of supply chain resilience levels.

Resource integration capability
This study aims to verify whether artificial intelligence (AI) policies can enhance corporate supply chain resilience by strengthening resource integration capabilities. Drawing on the research of Zhang et al., we use ln(365/inventory turnover ratio) to measure a company's resource integration capability[35]. The inventory turnover ratio reflects the efficiency of a company's inventory management. A higher turnover ratio indicates a faster inventory turnover speed, which is a direct manifestation of cross - regional resource flow. By introducing the constant of 365 days and dividing it by the inventory turnover ratio, we can transform the inventory turnover ratio into an indicator that measures the average number of days required for a complete inventory turnover on an annual basis. This makes it easier for intuitive understanding and horizontal comparison of the resource integration and operation speeds of different companies. As shown in columns (4) and (5) of Table 7, the estimated coefficients of AI policies on resource integration capabilities and of resource integration capabilities on corporate supply chain resilience are 0.0319 and 0.0024, respectively, and both have passed the significance tests at the 5% and 10% levels. In column (6), after simultaneously introducing AI policies and resource integration capabilities, the regression coefficients of both on corporate supply chain resilience remain significantly positive, indicating that AI policies can promote the enhancement of corporate supply chain resilience by strengthening resource integration capabilities. Relying on Internet of Things (IoT) technologies and intelligent algorithms, AI policies effectively improve a company's ability to integrate information and material resources, successfully resolving the dilemmas faced during the process of resource acquisition. When the supply chain is subjected to external shocks, these policies can promote resource collaboration and integration among companies, thereby mitigating

Variables	Absorption capacity			Resource integration capability			Innovation ability		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Abs	*Sup*	*Sup*	*Int*	*Sup*	*Sup*	*Inn*	*Sup*	*Sup*
AI	0.5062***		0.0158***	0.0319**		0.0163***	0.2052***		0.0125***
	(0.0489)		(0.0028)	(0.0162)		(0.0028)	(0.0202)		(0.0030)
Abs		0.0009**	0.0007*						
		(0.0003)	(0.0003)						
Int					0.0024*	0.0025*			
					(0.0014)	(0.0014)			
Inn								0.0038***	0.0034***
								(0.0011)	(0.0011)
95%CI	[0.4104,0.6019]	[0.0002,0.0015]	[0.0103,0.0213]	[0. 0002, 0.0636]	[−0.0002,0.0051]	[0 0.0109,0.0218]	[0.1657,0.2447]	[0.0016,0.0059]	[0.0066,0.0184]
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control²	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	22,188	22,188	22,188	22,188	22,188	22,188	22,188	22,188	22,188

Table 7. Mechanism Test.

the risk of supply chain disruptions, stabilizing demand fluctuations, and contributing to the construction of a supply chain system with stronger risk - resistance capabilities and higher stability.

Innovation ability
This study aims to verify whether artificial intelligence (AI) policies can enhance supply chain resilience by promoting innovation capabilities. Drawing on the approach of Yao et al., we measure a firm's innovation capability by taking the natural logarithm of the number of granted patent applications plus one47. The number of granted patent applications objectively represents the effective output of a firm's technological innovation achievements, encompassing both the quantity and technological value of innovation. The "plus one" treatment is adopted to circumvent the statistical challenge of taking logarithms when some firms have zero patent authorizations during specific periods, thereby avoiding the impact of missing samples on the integrity of the study. As shown in the results of columns (7) and (8) of Table 7, the regression coefficients of AI policies on innovation capability and of entrepreneurial capability (assuming it's a possible mis - mention and should be innovation capability here for context consistency, if it's really entrepreneurial capability, the following needs to be adjusted accordingly) on corporate supply chain resilience are 0.2052 and 0.0038, respectively, and both have passed the 1% significance test. In column (9), after simultaneously introducing AI and innovation capability, the regression coefficients of both on supply chain resilience remain significantly positive, indicating that AI policies can enhance corporate supply chain resilience by improving resource integration capabilities. AI policies provide direction for firm innovation through technological embedding. At the same time, the policies themselves act as incubators, creating a favorable ecosystem for firm innovation. The improvement in a firm's innovation capability not only enables it to adapt to the dynamic market demands in multiple ways but also integrates innovative elements into various links of the supply chain, enhancing the operational efficiency of supply chain entities while also strengthening their stability.

Test of moderating effect

As can be inferred from the preceding analysis, artificial intelligence (AI) policies play a significant role in promoting the enhancement of corporate supply chain resilience. To advance the improvement of supply chain resilience, it is imperative to seize the opportunities presented by AI development. However, the widespread application of AI in the supply - chain system necessitates digitalization as a foundation and capital investment as a guarantee to ensure effective technology implementation and drive supply - chain optimization and upgrading. Under such circumstances, at the macro level, regional financial subsidies provide the necessary capital support for the continuous promotion and application of AI in the supply - chain field, while the regional digitalization level offers the essential technological support for AI development. At the micro level, a company's research and development (R&D) investment directly influences the depth and breadth of AI R&D and application. Moreover, a company's digital transformation is closely related to the development potential of AI and the implementation of supply - chain intelligence. Then, what kind of moderating effect do the digitalization levels and capital support at the regional and enterprise levels have on the relationship between AI and supply - chain resilience? Can the expected results be achieved? To answer these questions, at the macro level, this paper selects the proportion of local fiscal expenditure in GDP to measure government subsidies and calculates a comprehensive digital economy index to measure the regional digitalization level (the indicators are shown in Appendix 2). At the micro level, the ratio of a company's development investment to its operating revenue is used to measure the R&D investment situation. For a company's digital transformation, after extracting the business - related text using Python, the samples are subjected to word segmentation and word - frequency statistics. High - frequency words related to digital transformation are screened out. These words are then classified into four aspects: digital technology application, Internet business models, intelligent manufacturing, and modern information systems. The results are calculated using the entropy method. A moderating effect model is constructed as follows for testing:

$$Sup_{it} = \rho_0 + \rho_1 AI \times R_{it} + \rho_2 AI_{it} + \rho_3 R_{it} + \rho_4 X_{it} + \sigma_i + \sigma_j + \sigma_t + \varepsilon_{it} \tag{14}$$

In Eq. (14),R_{it}serves as the moderating variable, and the settings of other variables remain the same as those in Model (6). Table 8 presents the impacts of capital support and digitalization levels at both the macro and micro levels on the influence of artificial intelligence (AI) on supply - chain resilience. The results show that the interaction terms between AI and the moderating variable are significantly positive at both the regional

	(1)	**(2)**	**(3)**	**(4)**
Variables	**Government subsidy**	**Regional digitalization level**	**Research and development investment**	**Enterprise digitalization**
AI×R	0.5210***	0.0941***	0.0266**	0.0033**
	(0.0606)	(0.0100)	(0.0105)	(0.0014)
95%CI	[0.4023,0.6397]	[0.0746,0.1137]	[0.0060,0.0471]	[0.0004,0.0061]
Control	Yes	Yes	Yes	Yes
Control^2	Yes	Yes	Yes	Yes
Fixed effect	Yes	Yes	Yes	Yes
N	22,188	22,188	22,188	22,188

Table 8. Analysis of the moderating effects of artificial intelligence on empowering Supply - Chain Resilience.

and enterprise levels, indicating that the levels of capital investment and digitalization can effectively enhance the promoting effect of AI on supply - chain resilience. The levels of digitization and capital investment at both the regional and enterprise levels serve as the foundation and guarantee for artificial intelligence (AI) to enhance supply chain resilience. From a regional perspective, the digital economy, with digital technology and information as its core production factors, creates favorable conditions for AI to function effectively. By utilizing sensors, AI can monitor real - time supply and demand information in the supply chain. When information is fully interacted, each node enterprise can swiftly adjust production plans based on accurate data, efficiently respond to market fluctuations and unexpected risks, and provide underlying support for supply chain risk anticipation, thereby facilitating AI in improving supply chain resilience. The policies such as financial subsidies and tax incentives introduced by the government offer capital support for regional AI development, promoting its widespread application in the supply chain field. The characteristics of high permeability, high integration, and high versatility of AI can be better exerted with the help of capital, expanding the connection methods of the supply chain, promoting collaborative cooperation among all parties, enhancing the supply chain's ability to withstand risks, and increasing its application scope. From an enterprise perspective, enterprise digital strategies and the underlying technologies of AI are highly homologous. During digital transformation, enterprises will improve, optimize, and innovate the underlying technologies for digital technology applications, generating a technology - inducing effect. This provides technical support for AI development and strengthens its promoting effect on supply chain resilience. The research and development (R&D) investment of enterprises in the AI field reflects their innovation capabilities and growth potential. Sufficient investment can optimize production processes, shorten process and production cycles, accelerate inventory turnover, reduce resource idleness, enhance supply chain collaboration and risk - response capabilities, and improve the stability of the supply system.

Heterogeneity tests

Test of urban heterogeneity

This paper employs sub - sample regression to examine the heterogeneous effects of artificial intelligence (AI) policies on enterprise supply chains, conducting grouping from the perspectives of regional heterogeneity and enterprise heterogeneity respectively. At the level of regional heterogeneity, a heterogeneity analysis framework is constructed based on two dimensions: urban location heterogeneity and economic development heterogeneity. Among them, urban location heterogeneity is divided into three dimensions according to the geographical location of cities: the eastern and central - western regions, the southern and northern regions, and the coastal and inland regions; economic development heterogeneity is tested from three aspects: city tier, digital infrastructure, and transportation infrastructure.

(1) Eastern and Central-Western Regions. Given the significant disparities in the level of economic development and industrial structure layout between the eastern and central - western regions of China, these differences result in varying artificial intelligence (AI) application environments across regions, which may consequently lead to differences in the impacts of AI across different areas. All samples are divided into eastern and central - western samples based on the geographical location of cities, and subgroup regression analysis is conducted. As can be seen from the results in columns (1) and (2) of Table 9, AI policies have a significant enabling effect on the resilience of enterprise supply chains in the eastern region, while their impact in the western region is not significant. The possible reasons are as follows: The eastern region has gathered a large number of high - tech enterprises and scientific research institutions, with abundant technological resources and a sufficient talent pool. This enables the efficient implementation of AI policies, thereby enhancing the resilience of enterprise supply chains. In contrast, the central - western regions face challenges such as relatively scarce technological resources and the outflow of professional talents, which to some extent restricts the positive promoting effect of AI policies on the resilience of enterprise supply chains.

(2) Southern and Northern Regions. Given the significant disparities in economic development patterns and technological innovation ecosystems between southern and northern China, the impact of artificial intelligence (AI) policies on the resilience of enterprise supply chains is highly likely to exhibit heterogeneous characteristics between the south and the north. The samples are divided into southern and northern parts based on the Qinling - Huaihe Line, and subgroup regression analysis is conducted. As can be seen from the results in columns (3) and (4) of Table 9, AI policies have significantly promoted the improvement of the resilience of enterprise supply chains in both the south and the north, and the promoting effect is stronger in the northern region.

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Variables	**East**	**Central and Western Regions**	**South**	**North**	**Coastal**	**Inland**
AI	0.0308***	−0.0071	0.0155***	0.0301**	0.0265***	−0.0049
	(0.0064)	(0.0095)	(0.0059)	(0.0134)	(0.0062)	(0.0100)
95%CI	[0.0181,0.0434]	[−0.0257,0.0115]	[0.0040,0.0270]	[0.0039,0.0563]	[0.0143,0.0387]	[−0.0245,0.0146]
Control	Yes	Yes	Yes	Yes	Yes	Yes
$Control^2$	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
N	15,732	6,456	15,508	6,680	16,359	5,829

Table 9. Test for urban location Heterogeneity.

The possible reasons are as follows: Traditional industries account for a relatively large proportion in the north and face more urgent pressure for transformation and upgrading. AI policies precisely meet the needs of its industrial innovation, enabling more direct and effective optimization of supply - chain links and enhancement of resilience. In contrast, the south has a diversified industrial structure, and some emerging industries have already reached a certain scale. The enhancing effect of AI on supply - chain resilience is relatively more stable.

(3) Coastal and Inland Regions. There are significant differences in the level of openness and types of logistics between coastal and inland areas. Therefore, the enhancing effect of artificial intelligence (AI) may exhibit structural heterogeneity in coastal and inland cities. Based on whether a city is adjacent to the sea, the samples are divided into coastal and inland groups, and subgroup regression analysis is conducted. As can be seen from the results in columns (5)-(6) of Table 9, AI policies have a positive impact on the improvement of the resilience of enterprise supply chains in coastal areas and pass the 1% significance test, while having no significant impact on inland areas. The possible reasons are as follows: Coastal areas have a diversified industrial structure and a well - developed export - oriented economy, with a high degree of integration with AI technology, enabling them to rapidly apply it to various links of the supply chain to enhance resilience. In contrast, inland areas have a relatively single industrial structure with a large proportion of traditional industries. The difficulty of matching AI with the existing supply - chain system is relatively high, so no significant impact is generated.

(4) Urban Hierarchy. Differences in urban hierarchy can lead to variations in infrastructure, factor agglomeration and allocation, which may result in heterogeneous manifestations of policy effects. Based on whether a city is a provincial capital or a municipality directly under the central government, the samples are divided into central cities and peripheral cities for regression analysis. As shown in columns (1) and (2) of Table 10, it can be observed that artificial intelligence (AI) policies can significantly promote the resilience of enterprise supply chains in both central and peripheral cities. However, the empowering effect on central cities is greater than that on peripheral cities. The possible reasons are as follows: Central cities, with a well - established industrial ecosystem formed by a high degree of resource agglomeration, can more efficiently absorb and transform the policy dividends of AI, achieving deep integration between technology and various links of the supply chain. In contrast, peripheral cities have a relatively weak industrial ecosystem, which limits the policy - empowering effect.

(5) Digital Infrastructure Construction. Digital infrastructure serves as a crucial hardware support for the development of artificial intelligence (AI). Its coverage breadth, technological advancement, and network stability play a decisive role in the application and innovation of AI. Based on the median number of Internet - connected users, the samples are divided into two groups: regions with high - level digital infrastructure and regions with low - level digital infrastructure, and then grouped regression analysis is conducted. The results show that AI policies have a significant promoting effect on supply chain resilience in regions with high - level digital infrastructure, while having no significant impact on cities with low - level digital infrastructure. The possible reasons are as follows: Regions with high - level digital infrastructure can provide a stable operating environment and powerful data transmission and processing capabilities for AI technologies, enabling them to be fully integrated into various links of the supply chain and thus enhancing enterprise supply chain resilience. In contrast, regions with low - level digital infrastructure struggle to support the effective application of AI technologies, resulting in an insignificant impact on supply chain resilience.

(6) Transport Infrastructure Construction. Transport infrastructure construction serves as a crucial safeguard for supply chain logistics. Its completeness, transportation efficiency, and coverage play a vital supporting and facilitating role in the flow of supply chain elements. The differences in its development directly affect the process - orientation, cost - effectiveness, and risk - response capacity of the overall supply chain operation. Based on the median value of highway mileage, the samples are divided into two groups: regions with high - level transport infrastructure and regions with low - level transport infrastructure, and then grouped regression analysis is conducted. As can be seen from the results in columns (5) and (6) of Table 10, the coefficient of the artificial intelligence (AI) policy in the group with high - level transport infrastructure is 0.0269, while the estimated coefficient in the group with low - level transport infrastructure is 0.0243. Therefore, AI policies are more conducive to enhancing the supply chain resilience in regions with high - level transport infrastructure. The possible reasons are as follows: Regions with high - level transport infrastructure have more developed logistics networks, enabling AI to deeply synergize with the efficient transportation system, rapidly optimize supply chain

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	**Central city**	**Peripheral cities**	**The digital infrastructure is high**	**The digital infrastructure is low**	**The transportation infrastructure is high**	**The transportation infrastructure is low**
AI	0.0515***	0.0274*	0.0582***	−0.0217	0.0269***	0.0243**
	(0.0106)	(0.0147)	(0.0126)	(0.0136)	(0.0080)	(0.0110)
95%CI	[0.0307,0.0722]	[−0.0014,0.0562]	[0.0335,0.0829]	[−0.0483,0.0049]	[0.0111,0.0426]	[0.0026,0.0459]
Control	Yes	Yes	Yes	Yes	Yes	Yes
$Control^2$	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
N	13,644	8,544	10,184	12,004	11,816	10,372

Table 10. Tests for heterogeneity in economic Development.

processes, and reduce losses. In contrast, regions with low - level transport infrastructure face numerous logistics bottlenecks, and the effectiveness of AI in improving supply chain resilience is constrained by logistics efficiency.

Tests for firm heterogeneity

At the level of enterprise heterogeneity, an analytical framework for heterogeneity is constructed from both static and dynamic perspectives. In the static perspective, heterogeneity tests are conducted based on the logical framework of enterprise - industry - market. It mainly focuses on the equity nature of enterprises, industry types, and market competition levels, and is divided into three dimensions: state - owned enterprises and non - state - owned enterprises, technology - intensive industries and labor - intensive industries, and high - market - competitiveness and low - market - competitiveness. In the dynamic perspective, based on the logical framework of intelligence - supply chain upstream - supply chain downstream, it is mainly divided into three aspects of heterogeneity: the development level of robots, supply concentration, and customer concentration.

(1) Ownership Nature. The promoting effect of artificial intelligence (AI) on the resilience of enterprise supply chains may vary in terms of property - right structure, resource acquisition mechanisms, and institutional constraints due to differences in equity nature. The sample is divided into two groups, namely state - owned enterprises (SOEs) and non - state - owned enterprises, based on the equity nature of enterprises, and a grouped regression is conducted. Columns (1) and (2) of Table 11 show that for both SOEs and non - SOEs, AI has a significant promoting effect on the resilience of enterprise supply chains. The difference lies in that the promoting effect on SOEs is stronger than that on non - SOEs. Possible reasons are as follows: SOEs usually benefit from preferential allocation of policy resources and hold a more secure position within the institutional environment. This institutional advantage enables SOEs to integrate digital infrastructure with upstream and downstream resources more efficiently. On one hand, government support policies for SOEs often involve substantial investments in digital infrastructure, such as the construction of advanced cloud computing centers and big data platforms, providing a solid hardware foundation for the application of AI technologies. On the other hand, SOEs usually occupy a dominant position in the industrial chain and maintain closer and more stable cooperative relationships with upstream and downstream enterprises. This facilitates smoother promotion of collaborative operations across various supply chain links when applying AI technologies, thereby enhancing supply chain resilience.

(2) Industry Type. Systematic differences exist among industries with varying technological levels in terms of technological foundation, market dynamics, and resource integration capabilities. Consequently, the impact of artificial intelligence (AI) on supply chain resilience varies across industries where enterprises are located. Based on the "National Key Supported High - Tech Fields," the sample is divided into two groups: skill - intensive industries and labor - intensive industries, and a grouped regression is conducted. Columns (3) and (4) of Table 11 reveal that for skill - intensive industries, AI has a significantly positive impact on enterprise supply chain resilience at the 1% level, while it has no significant impact on labor - intensive industries. Possible reasons are as follows: Skill - intensive industries boast more well - established technological infrastructures and knowledge spillover effects. The government has made substantial innovation investments in this industry, promoting industry - university - research cooperation among universities, research institutions, and enterprises, and cultivating a large number of high - quality technical talents for the industry. These talents not only possess solid professional knowledge but can also quickly master and apply AI technologies, integrating them into the supply chain management process. In contrast, labor - intensive industries mainly rely on traditional production methods, with relatively weak technological innovation capabilities. Their ability to integrate digital technologies with supply chain management processes is limited, making it difficult to fully leverage AI technologies to enhance supply chain resilience. Therefore, AI can generate stronger marginal effects in skill - intensive industries.

(3) Differences in Market Competitiveness. Under varying competitive environments, firms exhibit heterogeneity in the extent to which they leverage artificial intelligence (AI) to optimize supply chain processes due to differences in survival pressures and efficiency demands. Following Guo, J. H. et al. (2023)[47], the sample is divided into two groups—high-market-competitiveness and low-market-competitiveness firms—using the median Herfindahl index as the threshold for subgroup regression analysis. As shown in Columns (5) and (6) of Table 11, AI significantly enhances supply chain resilience for firms in highly competitive markets, while exhibiting no statistically significant impact on those in less competitive markets. The potential explanation lies in the fact that firms under intense market competition face greater technological iteration pressures, leading

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	**State-owned enterprise**	**Non-state-owned enterprises**	**High-tech industry**	**Non-high-tech industries**	**The market competition is fierce.**	**The market competition is small.**
AI	0.0388***	0.0120**	0.0168***	0.0069	0.0203***	0.0123*
	(0.0097)	(0.0060)	(0.0063)	(0.0081)	(0.0068)	(0.0074)
95%CI	[0.0199,0.0577]	[0.0002,0.0239]	[0.0044,0.0292]	[−0.0089,0.0227]	[0.0069,0.0337]	[−0.0022,0.0268]
Control	Yes	Yes	Yes	Yes	Yes	Yes
$Control^2$	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
N	7,031	15,157	11,974	10,214	10,763	11,425

Table 11. Test for heterogeneity in static Attributes.

to higher investments in AI development and diversified supply systems, which substantially improve supply chain resistance. Conversely, firms in low-competition markets experience smaller risk exposures and lack endogenous incentives for "chain expansion" or "chain supplementation," resulting in a less pronounced effect of urban digital transformation on supply chain resilience enhancement.

(4) Applications of Intelligent Robots. Differential levels of intelligent robot adoption may lead to variations in cost reduction and efficiency enhancement among firms, resulting in heterogeneous impacts of corporate AI development on supply chains. Drawing on the study by Zhang, Y. L. et al. (2025)[48], we measure the penetration rate of industrial robots, divide the samples based on the median, and then conduct grouped regression. Columns (1)–(2) in Table 12 reveal that artificial intelligence policies have a more pronounced promoting effect on enhancing the supply - chain resilience of enterprises with a higher degree of robot application. This is because enterprises with a high level of robot application, equipped with more mature automation infrastructure and digital integration capabilities, can more efficiently accommodate the algorithm optimization and process reengineering of artificial intelligence, thereby releasing stronger technological synergy premiums in supply - chain risk response.

(5) Supplier Concentration. Firms with high supplier concentration, which rely on a limited number of core suppliers, can more effectively optimize the resilience of critical nodes through technological empowerment. In contrast, firms with dispersed suppliers achieve dynamic equilibrium in multi-source networks via technological penetration, demonstrating differentiated adaptive effects in resilience enhancement pathways. Drawing on He, H. H. et al. (2023)[49], supplier concentration is measured by the proportion of procurement expenditure from the top five suppliers. As shown in Columns (3)-(4) of Table 12, artificial intelligence (AI) exerts positive effects on supply chain resilience in both high- and low-concentration firms, with statistical significance at the 1% level. However, its empowering effect is more pronounced in high-concentration firms. This is because firms with high supplier concentration exhibit strong dependency on critical nodes, enabling technological empowerment to deeply enhance core suppliers' collaboration efficiency and risk early-warning capabilities. Conversely, firms with low concentration face diluted marginal returns from technological investments due to coordination costs in multi-source networks, resulting in a more significant resilience enhancement effect in the former group.

(6) Customer Concentration. Firms with high customer concentration may focus on deepening collaborative capabilities with key customers due to stronger demand predictability, whereas firms with dispersed customer bases are more likely to prioritize dynamic equilibrium across multiple customer segments and demand adaptation flexibility. These two types of firms may exhibit differentiated choices in technology-enabled pathways. Following He, H. H. et al. (2023), customer concentration is measured by the proportion of procurement volume from the top five customers[49]. As shown in Columns (5)-(6) of Table 12, artificial intelligence significantly enhances supply chain resilience for both firms with high and low customer concentration, with a stronger effect observed in firms with high customer concentration. This is because firms with high customer concentration benefit from relatively stable demand structures and strong bargaining power of key customers, allowing technological investments to concentrate on optimizing core customer response mechanisms and long-term partnership stability. In contrast, firms with dispersed customer bases face higher demand heterogeneity and coordination costs, diluting the precision of technological empowerment. Consequently, the resilience-enhancing effect is more pronounced in the former group.

Further analysis

The impact of artificial intelligence on supply chains when facing disruptions

The impact of exogenous shocks on supply chain resilience During the sample research period, the COVID-19 pandemic that broke out in 2019 exerted the most significant impact on the supply chain system, causing the fragmentation and collapse of the global supply chain system. This section takes the COVID-19 pandemic as a major shock and explores the impact of public health events on the supply chain system. The estimation results in Table 13 indicate that shocks can enhance the resilience level of the supply chain. Moreover, they have a significant improving effect on the adaptability of the supply chain (a negative indicator), but reduce its resistance capacity. This suggests that shocks have a complex impact on the supply chain. From the perspectives of supply chain resilience and adaptability, when facing difficulties such as drastic changes in market demand and supply chain disruptions, enterprises actively adjust their strategies to adapt to the environment and reduce losses. They specifically produce products that are in urgent market demand and have relatively stable profits to quickly adapt to new demands and reduce losses from inventory backlogs. For example, during the pandemic in China, due

Variables	(1) More robots	(2) Fewer robots	(3) High supply concentration	(4) Low supply concentration	(5) High customer concentration	(6) Low customer concentration
AI	0.0269***	0.0100	0.0154**	0.0140**	0.0200***	0.0106
	(0.0083)	(0.0067)	(0.0074)	(0.0070)	(0.0071)	(0.0072)
95%CI	[0.0108,0.0431]	[−0.0031,0.0230]	[0.0009,0.0299]	[0.0002,0.0278]	[0.0061,0.0339]	[−0.0035,0.0247]
Control	Yes	Yes	Yes	Yes	Yes	Yes
Control^2	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
N	9,889	12,299	10,509	11,679	11,889	10,299

Table 12. Test for heterogeneity in dynamic Capabilities.

Variables	(1) Supply Chain Resilience	(2) Supply Chain Resistance Capacity	(3) Supply Chain Adaptability	(4) Supply Chain Resilience
COVID-19	0.0118***	−0.0123***	−0.0175***	0.0256
	(0.0037)	(0.0044)	(0.0037)	(0.0295)
95%CI	[0.0045,0.0191]	[−0.0209,−0.0037]	[−0.0249,−0.0103]	[−0.0323,0.0835]
Control	Yes	Yes	Yes	Yes
Control^2	Yes	Yes	Yes	Yes
Fixed effect	Yes	Yes	Yes	Yes
N	22,188	22,188	22,188	22,188

Table 13. Impact of exogenous shocks on supply chain Resilience.

Variables	(1) Supply Chain Resilience	(2) Supply Chain Resistance Capacity	(3) Supply Chain Adaptability	(4) Supply Chain Resilience
COVID-19_AI	0.0171***	−0.0014	−0.0300***	0.0106
	(0.0058)	(0.0040)	(0.0095)	(0.0371)
95%CI	[0.0057,0.0284]	[−0.0093,0.0065]	[−0.0487,−0.0113]	[−0.0620,0.0833]
Control	Yes	Yes	Yes	Yes
Control^2	Yes	Yes	Yes	Yes
Fixed effect	Yes	Yes	Yes	Yes
N	22,188	22,188	22,188	22,188

Table 14. The Chain-Stabilizing effect of artificial intelligence under the COVID-19 pandemic Shock.

to the shortage of medical protective equipment, various industries began to shift their production to masks, protective suits, and disinfection products, demonstrating the adaptability of enterprises during shocks. From the perspective of the supply chain's resistance capacity, the suddenness and widespread nature of the COVID-19 pandemic have exposed the supply chain to an unprecedented risk of large-scale disruptions. The existing supply chain layout and risk management measures of enterprises are difficult to cope with such severe external shocks, leading to a continuous decline in their resistance capacity.

The mitigating effect of artificial intelligence on shocks

To verify whether artificial intelligence (AI) policies can mitigate the impact of exogenous shocks on supply chains. Building upon the preceding content, we further examine the role of AI in "stabilizing supply chains" by incorporating the interaction between AI and exogenous shocks. As evident from Table 14, the estimated coefficients increase after the inclusion of the interaction term for AI policies, indicating that AI policies can reduce the impact of exogenous shocks and thus play a role in stabilizing supply chains. Moreover, the significant impact on supply - chain resilience is offset, and the promoting effect on adaptability is enhanced, further bolstering the reliability of our argument. However, as shown in Column (4), AI policies do not exert a significant impact on supply - chain recovery. The likely reason is that during the initial phase of the pandemic shock, its transmission speed and scope of impact far exceeded expectations, leading to disruptions in the data - collection system. Due to the lack of valid data, AI models struggle to accurately analyze the extent of market impact, thereby failing to make precise decisions regarding supply recovery. Consequently, the mitigating effect of AI policies on the recovery capacity of supply chains under exogenous shocks is not significant.

Heterogeneous impacts of artificial intelligence in responding to shocks across different periods

T To further examine the impact of artificial intelligence (AI) policies on the resilience of enterprise supply chains during different shock periods, the sample is divided into the initial shock period and the later shock period for testing. As shown in Table 15, during the initial shock period, AI policies do not have a significant impact on supply - chain resilience and the capabilities across various dimensions of the supply chain. However, they can empower the improvement of supply - chain resilience in the later period and have a significant strengthening effect on the capabilities in the dimensions of resistance and adaptability. The possible reason is that the shock erupts suddenly with an unclear form, and each node in the supply chain faces multiple urgent and complex issues such as production halts, logistics disruptions, and sudden changes in demand. At this time, enterprises mainly focus on addressing immediate survival crises, such as ensuring basic production, maintaining employee stability, and preventing the disruption of the capital chain. They lack sufficient time and resources to deeply explore and effectively apply AI technologies. As enterprises' understanding of the shock deepens, they gradually transition from the initial stress state to a long - term strategic adjustment and optimization phase. Meanwhile, at this stage, AI development has entered a relatively mature phase, and the pandemic situation is basically under control. Enterprises have ample time and resources to promote the deep integration of AI with supply - chain operations. In addition, the recovery capacity of supply chains involves rapid restoration after major shocks,

Variables	Early Stage of Shock (2018–2020)				Late Stage of Shock (2021–2023)			
	Supply Chain Resilience	Supply Chain Resistance Capacity	Supply Chain Adaptability	Supply Chain Resilience	Supply Chain Resilience	Supply Chain Resistance Capacity	Supply Chain Adaptability	Supply Chain Resilience
AI	0.0117	0.0177	−0.0080	−0.0786	0.0217***	0.0290***	−0.0185***	−0.0331
	(0.0097)	(0.0152)	(0.0083)	(0.1034)	(0.0076)	(0.0102)	(0.0045)	(0.0419)
95%CI	[−0.0073,0.0307]	[−0.0121,0.0474]	[−0.0243,0.0083]	[−0.2812,0.1241]	[0.0068,0.0366]	[0.0090,0.0490]	[−0.0272,−0.0097]	[−0.1152,0.0491]
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$Control^2$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	7,403	7,403	7,403	7,403	10,918	10,918	10,918	10,918

Table 15. Impacts of artificial intelligence on supply chains during the early and late stages of Shocks.

First-level indicator	Secondary indicators	Measurement method	Unit
Resistance	Economic scale	Gross domestic Product	Ten thousand yuan
		Industrial added value	Ten thousand yuan
	Economic effect	General public budget revenue	Ten thousand yuan
Adaptability	Technological innovation	The number of patent applications authorized	a
	Digital level	Internet users	a
Resilience	Market entities	The number of industrial enterprises above designated size	a
	Financial efficiency	Total profits of industrial enterprises above designated size	Ten thousand yuan
		Current assets of industrial enterprises above designated size	Ten thousand yuan

Table 16. Indicators for measuring supply chain Resilience.

which requires adjustments across multiple dimensions including production factors, customers, and logistics. Some small and medium - sized enterprises (SMEs), affected by the shock, have not fully recovered and exerted their functions, and are unable to effectively provide physical - level support for AI - based decision - making. As a result, AI cannot effectively serve to enhance the recovery capacity of supply chains. The final results confirm the issues identified above and also conform to real - world logic.

The Spatial spillover effects of artificial intelligence on supply chain resilience

Measurement of supply chain resilience at the urban level

To further examine the spatial spillover effects of artificial intelligence (AI) policies on the resilience of enterprise supply chains, referring to the research of Gao et al., we conduct a spatial spillover effect test by constructing and measuring the supply - chain resilience level at the prefecture - level city level[50]. Combining the indicator system of provincial - level supply - chain resilience in China proposed by Wang et al.[51], considering data availability and integrating the three dimensions of supply - chain resilience measurement mentioned earlier, we extend it to the urban level in China. We construct an urban - level supply - chain resilience indicator system from the perspectives of supply - chain resistance capacity, adaptability capacity, and recovery capacity (see Table 16). The control variables selected are as follows: the logistics level (Flo) is measured by the total volume of highway freight transport; the market size (Mar) is measured by the total retail sales of consumer goods; foreign trade (Tra) is measured by the total value of goods imports; and commodity imports (Imp) is measured by the total value of goods exports. After taking the natural logarithms of the above - mentioned variables, they are included in the regression model.

Research methods

Commonly used spatial econometric models primarily include the Spatial Autoregressive (SAR) model, the Spatial Error Model (SEM), and the Spatial Durbin Model (SDM). The identification of these models mainly relies on statistical methods such as the Lagrange Multiplier (LM) test, the Likelihood Ratio (LR) test, and the Wald test. Prior to conducting an analysis of spatial spillover effects, it is first necessary to use Moran's I index to test for the presence of spatial autocorrelation in supply - chain resilience. The formula for calculating Moran's I index is as follows:

$$I = \frac{\sum_{i}^{n}\sum_{j\neq 1}^{n} w_{ij}(Sup_i - \overline{Sup})(Sup_j - \overline{Sup})}{s^2 \sum_{i}^{n}\sum_{j\neq 1}^{n} w_{ij}} \tag{15}$$

In Eq. (15), I denotes Moran's I index.Sup_i represents the level of supply - chain resilience in city i.$\overline{Sup}$indicates the mean value of supply - chain resilience across all cities.$s^2$is the variance of Sup, and$w_{ij}$is the spatial weight matrix.

This paper employs three types of matrices, namely the adjacency matrix, the economic - distance matrix, and the geographical - distance matrix, to conduct tests on spatial spillover effects. The calculation formulas are presented as follows respectively:

$$w_{ij} = \begin{cases} 1, \text{Region i is adjacent to Region j} \\ 0, \text{Region i is not adjacent to Region j} \end{cases} \tag{16}$$

$$w_{ij} = \begin{cases} \dfrac{1}{x_1 - x_j}, i \neq j \\ 0, i = j \end{cases} \tag{17}$$

$$w_{ij} = \begin{cases} \dfrac{1}{d_{ij}^2}, i \neq j \\ 0, i = j \end{cases} \tag{18}$$

Equation (16) presents the calculation formula for the adjacency matrix, which is derived by determining whether two cities share a common border. Equation (17) represents the economic - distance matrix, wherex_i and$x_j$respectively denote the average GDP of City *i* and *j* City over the period from 2016 to 2023. Equation (18) is the geographical - distance matrix, withd_{ij}representing the distance between the spatial cross - sections of City *i* and City *j*.

Finally, the following spatial econometric models are established to test the spatial spillover effects of artificial intelligence on supply - chain resilience:

$$Sup_{it} = \phi_0 + \rho w \times Sup_{it} + \phi_1 AI_{it} + \phi_2 X_{it} + \sigma_i + \sigma_t + \varepsilon_{it} \tag{19}$$

Research findings and analysis

First, based on the adjacency matrix, economic - geographic matrix, and geographical inverse - distance matrix calculated from Eqs. (16)–(17), Moran's I index is computed using Eq. (15) to conduct a spatial autocorrelation test (see Table 17). This is done to explore the spatial correlation of supply - chain resilience. The results show that under different spatial weight matrices, the spatial autocorrelation coefficients of supply - chain resilience are all significantly positive at the 1% level, indicating the existence of a spatial autocorrelation relationship and the suitability for conducting a spatial spillover effect test.

Analysis of spatial spillover effects

Furthermore, we employ the Lagrange Multiplier (LM) test, Likelihood Ratio (LR) test, Wald test, and Hausman test for the selection of spatial econometric models (see Table 18). It is evident that the LM test, LR test, and Wald test all pass the significance tests, rejecting the null hypotheses that the Spatial Durbin Model (SDM) degenerates into the Spatial Autoregressive (SAR) model and the Spatial Error Model (SEM). Additionally, the Hausman test results indicate that a fixed - effects model should be used for the analysis. Therefore, we select the two - way

	Adjacency matrix	Economic distance matrix	Geographical distance matrix
year	Moran's I	Moran's I	Moran's I
2016	0.308***	0.208***	0.199***
	(8.055)	(7.232)	(11.390)
2017	0.308***	0.209***	0.201***
	(8.047)	(7.281)	(11.476)
2018	0.310***	0.210***	0.203***
	(8.075)	(7.296)	(11.628)
2019	0.317***	0.207***	0.208***
	(8.237)	(7.217)	(11.911)
2020	0.326***	0.209***	0.215***
	(8.439)	(7.269)	(12.308)
2021	0.328***	0.213***	0.216***
	(8.449)	(7.383)	(12.335)
2022	0.330***	0.215***	0.221***
	(8.500)	(7.448)	(12.583)
2023	0.337***	0.212***	0.224***
	(8.667)	(7.372)	(12.770)

Table 17. Spatial autocorrelation tests under different Matrices. Note: The values in parentheses are z-scores.

Variables	(1) Adjacency matrix	(2) Economic distance matrix	(3) Geographical distance matrix
AI	0.0426***	0.0405***	0.0416***
	(0.0019)	(0.0019)	(0.0018)
AI×W	0.0084**	0.0546***	0.0604***
	(0.0041)	(0.0059)	(0.0092)
Direct effect	0.0444***	0.0431***	0.0456***
	(0.0020)	(0.0019)	(0.0019)
Indirect effect	0.0302***	0.0879***	0.2233***
	(0.0051)	(0.0069)	(0.0272)
Overall effect	0.0746***	0.1311***	0.2689***
	(0.0060)	(0.0074)	(0.0278)
rho	0.3197***	0.2729***	0.6175***
	(0.0251)	(0.0407)	(0.0401)
sigma2_e	0.0001***	0.0001***	0.0001***
	(0.0000)	(0.0000)	(0.0000)
LM-Error	151.111***	0.505	275.051***
R-LM-Error	96.917***	4.849**	132.376***
LM-Lag	54.301***	1.826	179.204***
R-LM-Lag	0.107	6.169**	36.528***
LR-Error	93.34***	150.36***	95.66***
LR-Lag	62.81***	46.59***	27.99***
Wald-Error	93.16***	155.84***	95.75***
Wald-Lag	63.80***	42.99***	27.19***
Hausman	116.66***	4025.89***	223.49***
R^2	0.0653	0.5790	0.2513
Log-L	7139.0141	7147.0436	7249.2522
N	2,288	2,288	2,288

Table 18. Test results of Spatial spillover Effects.

fixed - effects Spatial Durbin Model to analyze the spatial spillover effects of artificial intelligence on supply chain resilience. The estimation results based on Eq. (19) are presented in Table 18. It can be observed that under different matrices, the overall and decomposed estimated coefficients of artificial intelligence are all significantly positive, indicating that the development of artificial intelligence not only enhances local supply chain resilience but also strengthens the supply chain resilience of neighboring regions through spatial transmission.

Discussion

Within the existing relevant content framework, this paper breaks away from the traditional research paradigm where the impact of artificial intelligence (AI) on supply - chain resilience is mostly focused on the micro - level[15]. Instead, it innovatively combines the enhancing effect of prefecture - level city AI policies on enterprise supply - chain resilience. For developing countries like China, local governments play a highly proactive role in the development of AI. In most developing countries, the development of AI is still in its infancy, with inadequate supporting facilities and a relative shortage of top - tier talents in the field[52]. Under such circumstances, if enterprises invest a large amount of funds in AI research and development, it will, to a certain extent, weaken their cash flow, reduce the flexibility of research and development resource allocation, and go against the strategic goals of their long - term development. Therefore, the government needs to actively play a guiding role through policy support to effectively promote the application of AI in the supply system.

Through the examination of mediating and moderating effects, this study systematically reveals the internal mechanisms and boundary conditions through which artificial intelligence (AI) policies empower enterprise supply - chain resilience, providing new empirical evidence for understanding the pathways to enhance supply - chain resilience in the digital economy era. The core research findings indicate that AI policies significantly enhance enterprise supply - chain resilience through three pathways: absorptive capacity, resource integration capacity, and innovation capacity. This echoes the research paradigm of Le et al. and simultaneously expands the dimensionality of mechanism research on the impact of policy tools on supply - chain resilience[53]. The mediating role of absorptive capacity demonstrates that knowledge absorption nodes formed by the aggregation of highly - educated talents are the key carriers for transforming AI technology into supply - chain risk - response capabilities. The transmission effect of resource integration capacity confirms the core value of the Internet of Things (IoT) and intelligent algorithms in breaking down barriers to resource flow and smoothing out supply - chain fluctuations. The mediating mechanism of innovation capacity highlights the incubating effect of policies on technological innovation, where the increase in patent output not only optimizes supply - chain operational efficiency but also strengthens its dynamic adaptability. These three pathways complement each other, jointly forming a complete logical chain of how AI policies influence supply - chain resilience. The results of the moderating effects further show that the regional digitalization level, government subsidies, enterprise R & D investment, and digital transformation jointly constitute important guarantees for policies to play their roles. This finding responds to the theoretical concern that technology implementation requires supporting infrastructure, indicating that the empowerment of AI on supply chains does not exist in isolation but depends on technological foundations and financial support at the macro level, as well as enterprise technological investment and strategic transformation at the micro level[54]. This provides key clues for explaining the differences in supply - chain resilience enhancement among different regions and enterprises.

The research innovatively constructs a dual - level heterogeneity analysis framework encompassing both regional and enterprise aspects. It not only covers macro - level dimensions such as urban location and development level but also involves micro - level characteristics like enterprise equity nature and technological foundation, breaking through the simplistic understanding of homogeneous policy effects in existing research. At the regional level, the study reveals that the supply - chain empowerment effect of artificial intelligence (AI) policies exhibits significant spatial heterogeneity. The policy effects are more pronounced in the eastern, coastal regions, and central cities, which is highly in line with the current development status of technological resource agglomeration in the eastern regions and the well - established industrial ecosystems in central cities. Notably, the policy effects in northern regions are stronger than those in southern regions. This finding complements traditional perceptions, confirms the crucial supporting role of AI technology in the transformation and upgrading of traditional industries, and provides new policy insights for optimizing the supply chains of old industrial bases in the north[55]. The heterogeneous effects of digital and transportation infrastructure indicate that technological application requires the support of sound hardware, which echoes the research conclusion of Cheng et al. regarding the enabling role of technological infrastructure in digital transformation[56]. The enterprise - level analysis further refines the boundaries of policy effects. State - owned enterprises and technology - intensive industries show higher policy sensitivity, reflecting the key role of property rights advantages and technological foundations in converting policy dividends. Enterprises with a high level of robot application demonstrate stronger synergistic premium effects, validating the complementarity between automation and AI technologies. The heterogeneous results of supplier and customer concentration show that the higher the degree of centralization of core stakeholders, the more significant the policy - enabling effects. This finding expands the research dimension of Liang et al. on the impact of supply - chain network structure on resource allocation efficiency[57].

Research on supply chain resilience has shifted from external strategies such as traditional redundancy allocation and redundant inventory to the deepening of internal dynamic adaptation mechanisms within the system[58]. However, existing theories have not fully integrated the core value of collaboration between artificial intelligence (AI) and humans, resulting in a disconnect between theory and supply chain practices in the digital age. Incorporating AI - human collaboration into the theoretical framework of supply chain resilience is not merely a superposition of technological applications. Instead, it reconstructs the path to resilience realization through the complementary mechanism of algorithmic efficiency + human judgment, which holds distinct theoretical innovation and practical guiding value. The scientific value of this emerging dimension lies primarily in resolving the systemic contradictions of information silos and decision - making lags in traditional supply chains. AI enables real - time data collaboration among multiple entities, accurate risk prediction, and dynamic resource matching through algorithms. Meanwhile, the irreplaceability of humans in value judgment in complex scenarios, ethical decision - making, and empathetic responses to emergencies can effectively compensate for the decision - making limitations caused by algorithm black boxes and data biases. The deep integration of the two can drive the upgrade of supply chain resilience from passive response to proactive prediction, forming a dual - wheel drive model of data - driven + cognition - enabled, which is highly in line with the development trend of human - centric intelligent systems advocated by Industry 5.0.

Research conclusions and policy implications

Against the backdrop of the intertwining of the digital economy and uncertainties in global supply chains, artificial intelligence (AI), as a disruptive technology, has emerged as a core driving force for enhancing supply chain resilience and withstanding external shocks by optimizing resource allocation and strengthening risk anticipation and dynamic response capabilities. However, for developing countries like China, there is insufficient attention paid to the impact of AI on supply chain resilience at the macro level. In particular, there is still a lack of in - depth exploration regarding the impact effects and mechanisms of AI policies. Meanwhile, the estimation of policy effects often employs the Difference - in - Differences (DID) method, which finds it difficult to effectively avoid interference from a large amount of irrelevant or redundant variable information in identifying key factors. This paper utilizes cross - level data from Chinese prefecture - level cities and A - share listed companies from 2016 to 2023, adopts the Double Machine Learning (DML) method, and is guided by the Dynamic Capabilities Theory. Based on theoretical reasoning and empirical evidence, the following conclusions are drawn: First, enterprises in AI pilot cities experience a more significant improvement in supply chain resilience levels. Second, AI policies can enhance the supply chain resilience of enterprises by strengthening their dynamic capabilities, and the digital foundation and financial support of regions and enterprises can reinforce the positive impact of AI policies on supply chain resilience. Third, there are significant differences in the impact effects of AI policies on supply chain resilience at both the city and enterprise levels. For cities or enterprises with inherent advantageous attributes and dynamic development potential, AI has a more pronounced strengthening effect on supply chain resilience. Fourth, further analysis reveals that shocks stimulate the improvement of supply chain resilience but lead to a decline in resistance capabilities. AI can mitigate the impact of epidemic shocks. Moreover, the enhancing effect of AI on supply chain resilience and its various - dimensional capabilities mainly emerges in the later stages of shocks. Additionally, AI can not only promote the improvement of supply chain resilience levels in pilot regions but also enhance the supply chain resilience of non - pilot enterprises through spatial spillover effects. Although this study systematically explores the impact of AI policies on supply chains and conducts detailed robustness tests from multiple dimensions, there may be issues such as policy selection bias, reliance on database data, and limited universality of conclusions. Future research can focus on multi - dimensional mining of AI proxy policy variables, collect company - level data, and carry out cross - country comparative studies to further deepen research in related fields.

Based on the aforementioned research findings, the following countermeasures and suggestions are proposed.

(1) Support and advance the deployment and research and development (R&D) of artificial intelligence (AI) in enterprises to unleash its promoting effect on supply chain resilience. During the process of the government promoting AI applications, it should increase investment in digital infrastructure construction, facilitate the transformation and upgrading of traditional infrastructure, and guide enterprises to enhance the application of AI technologies through preferential policies, thereby opening up channels for AI to boost supply chain resilience. Enterprises should actively respond to the national call, rely on the policy advantages of pilot cities, deploy typical intelligent scenarios in key node enterprises in sectors such as manufacturing, logistics, and energy, and promote the close integration of technology and production. Taking stronger environmental adaptability and better recognition accuracy as the evolutionary directions, enterprises should advance the breakthroughs in general AI technologies and continuously deepen the application of AI in supply chains.

(2) Enterprises should actively seize the new opportunities created by AI policies for enhancing dynamic capabilities and regard them as effective tools to strengthen supply chain resilience. Firstly, enterprises need to increase investment in the recruitment and cultivation of highly educated talents, establish a high - density intellectual capital system, and promote the transformation process from tacit knowledge to explicit knowledge, thereby enhancing the enterprise's knowledge absorption capacity. Secondly, on the basis of building information - sharing platforms, enterprises should be encouraged to jointly construct a flexible and efficient resource allocation mechanism, actively engage in resource exchange and cooperation with external enterprises, achieve the optimal allocation and efficient utilization of resources in a broader scope, and strengthen their resource integration capabilities. Finally, enterprises should focus on core business scenarios, develop dedicated algorithm models tailored to their own needs, accelerate the transformation and application of technological achievements into product iteration and process optimization, and enhance their overall innovation capabilities.

(3) Implement differentiated urban and enterprise development strategies to foster a development pattern of complementary strengths. During the process of advancing AI policies, it is essential to fully consider urban location factors, rationally plan urban spatial structures, and fully leverage the comparative advantages of cities in different regions to promote more adequate and balanced development among regions. Meanwhile, it is necessary to accelerate the cultivation of central cities and the improvement of infrastructure in peripheral cities. Lead the coordinated development of regional supply chains through multi - core AI construction, laying a foundation for enhancing supply chain resilience. Enterprises need to formulate differentiated development directions based on their corporate attributes as well as the externality characteristics of their industries and markets. State - owned enterprises, technology - intensive industries, and enterprises with strong market competitiveness should, on the basis of deploying AI application scenarios, further strive for innovative breakthroughs in AI technologies, ensure technological iteration and upgrading, and establish a replicable development model. In addition, enterprises should increase investment in intelligent equipment in the production process internally and build an external supply - demand cooperation system with high adaptability and moderate decentralization, achieving an advanced level of risk - resistance capacity through the synergy of technological application and network structure.

(4) Construct an AI - driven "Risk - Opportunity" dual - module system for supply chains to achieve the coordinated advancement of development and security. Enterprises should not only rely on AI - based early - warning and response systems for supply chain disruptions to enhance their capabilities in preventing and resolving supply chain risks. They should also transform the data of disruption risks and opportunities, utilize the deep - learning capabilities of AI to optimize algorithms for technological iteration, and seek potential development opportunities, thereby achieving an advanced level of supply chain resilience. In addition, close attention should be paid to the connections among cities within the region. Technical spillover channels should be established, and the concept of a supply - system community should be encouraged to continuously strengthen the "good - neighbor" effect.

Limitations of the study and future research directions

Although this study provides empirical evidence on the impact mechanism of AI policies on supply - chain resilience through cross - level data and double machine learning models, there are still several limitations as follows: First, the samples in this study focus on enterprise practices in the Chinese context. Therefore, the generalizability of the conclusions at the international level remains to be further verified. Future research can conduct cross - country comparisons and institutional context analyses to further expand the external validity and theoretical boundaries of the research conclusions. Second, the empirical analysis of this study mainly relies on indirect measurement data from public databases, lacking first - hand survey data and qualitative validation at the enterprise level. This may limit the measurement accuracy of some core variables and make it difficult to fully capture the dynamic process of the interaction between policy implementation and enterprise behavior. In the future, first - hand survey data and case study methods can be introduced. Micro - evidence on the application of AI technology and the improvement of supply - chain resilience can be obtained through enterprise interviews, field research, and other means, which can mutually confirm with the results of quantitative analysis. This not only compensates for the limitations of indirect measurement data but also provides a more in - depth analysis of the micro - operation mechanism of policy implementation, enhancing the persuasiveness and practical guiding value of the research conclusions. Finally, although this study attempts to mitigate estimation bias through model specification and robustness tests, there may be unobserved policy selection biases between the implementation of AI policies and the improvement of enterprise supply - chain resilience, which may still lead to endogenous risks in causal identification and thus affect the accuracy of the conclusions. Future research can focus on the synergistic effects of AI with emerging technologies such as blockchain and the Internet of Things, and analyze the additive empowerment paths of technology combinations on supply - chain resilience, providing more practical references for the optimization of enterprise technology application strategies.

Data availability

The data utilized in this study are sourced from China's national open-access databases. Given the need for subsequent publication of these datasets, they are not fully publicly available; however, interested researchers may request access from the corresponding author via email.

Received: 28 September 2025; Accepted: 7 December 2025
Published online: 07 February 2026

References

1. Zhong, Y. F., Chen, X. S., Wang, Z. X. & Lin, R. F. Y. The nexus among artificial intelligence, supply chain and energy sustainability: A time-varying analysis. *Energy Economics* **132**, 107479 (2024).
2. Song, Y. G., Wang, Z. Q., Song, C. Q., Wang, J. H. & Liu, R. Impact of artificial intelligence on renewable energy supply chain vulnerability: Evidence from 61 countries. *Energy Economics* **131**, 107357 (2024).
3. Jauhar, S. K. et al. How to use no-code artificial intelligence to predict and minimize the inventory distortions for resilient supply chains. *Int. J. Prod. Res.* **62** (15), 5510–5534 (2024).
4. Isgüzar, S., Fendoglu, E. & Simsek, A. I. Innovative applications in businesses: An evaluation on generative artificial intelligence. *Amfiteatru Economic* **26**(66), 511-530 (2024).
5. Li, J., Yi, M. & Sun, Q. Artificial intelligence and supply chain risk: mediating effects of supply chain efficiency and resilience. *International Rev. Financial Analysis* **108**, 104700 (2025).
6. Ma, L. Y., Luo, X. C. & Xi, M. N. The impact of regional artificial intelligence development on the resilience of enterprise supply chains. *International Rev. Econ. & Finance* **102**, 104305 (2025).
7. Zhou, C. B. et al. Artificial intelligence and green transformation of manufacturing enterprises. *International Rev. Financial Analysis* **104**, 104330 (2025).
8. Wang, Y., Wang, Y. H. & Yang, P. Y. Does artificial intelligence impact corporate ESG performance? Evidence from a quasi-natural experiment in China. *Energy Economics* **151**, 108963 (2025).
9. Zhu, K. J., Qiu, X. H., Yang, S. M., Zeng, Y. & Zhang, X. Y. The impact of AI pilot zones on market competition: causal insights from policy implementation. *Oeconomia Copernicana*. **16** (2), 643–688 (2025).
10. Zheng, M. Z., Wang, R., Ye, J. & Li, T. How does supply chain finance enhance firms' supply chain resilience? *International Rev. Econ. & Finance* **102**, 104231 (2025).
11. Qi, R. J., Ma, G. W., Liu, C., Zhang, Q. W. & Wang, Q. Y. Enterprise digital transformation and supply chain resilience. *Finance Res. Letters* **66**, 105564 (2024).
12. Li, Y. Y., Zhang, Y. D. & Geng, L. P. Digital finance, financing constraints and supply chain resilience. *International Rev. Econ. & Finance* **96**, 103545 (2024).
13. Pan, H., Zou, N., Wang, R. Y., Ma, J. C. & Liu, D. P. Artificial Intelligence Usage and Supply Chain Resilience: An Organizational Information Processing Theory Perspective. *Systems*.13(9), (2025).
14. Zogaan, W. A., Ajabnoor, N. & Salamai, A. A. Leveraging deep learning for risk prediction and resilience in supply chains: insights from critical industries. *Journal Big Data* **12**, 94 (2025).
15. Guo, X. C., Chen, Y., Xie, J. P., Wang, H. Y. & Lei, X. Research on supply chain resilience mechanism of AI-Enabled manufacturing enterprises -based on organizational change perspective. *Scientific Reports* **15**(1), 31177 (2025).
16. Yue, X. C., Kang, M. & Zhang, Y. M. The impact of artificial intelligence usage on supply chain resilience in manufacturing firms: a moderated mediation model. *J. Manuf. Technol. Manage.* **36** (4), 759–776 (2025).
17. Hu, R. Y., Bao, Z. M. H., Lin, Z. S. & Lv, K. The Innovative Construction of Provinces, Regional Artificial Intelligence Development, and the Resilience of Regional Innovation Ecosystems: Quasi-Natural Experiments Based on Spatial Difference-in-Differences Models and Double Machine Learning. *Sustainability*.16(18), (2024).
18. Zamani, E. D., Smyth, C., Gupta, S. & Dennehy, D. Artificial intelligence and big data analytics for supply chain resilience: a systematic literature review. *Ann. Oper. Res.* **327** (2), 605–632 (2023).
19. Shahin, M., Hosseinzadeh, A. & Chen, F. F. AI-Enabled Sustainable Manufacturing: Intelligent Package Integrity Monitoring for Waste Reduction in Supply Chains. *Electronics*.14(14), (2025).
20. Klar, R., Fredriksson, A. & Angelakis, V. Digital twins for ports: derived from smart City and supply chain twinning experience. *Ieee Access*. **11**, 71777–71799 (2023).
21. Wang, C. L. & Ahmed, P. K. Dynamic capabilities: A review and research agenda. *Int. J. Manage. Reviews*. **9** (1), 31–51 (2007).
22. Teece, D. J. Explicating dynamic capabilities: the nature and microfoundations of (sustainable) enterprise performance. *Strateg. Manag. J.* **28** (13), 1319–1350 (2007).
23. Shirazi, B. Towards a sustainable interoperability in food industry small & medium networked enterprises: distributed service-oriented enterprise resources planning. *J. Clean. Prod.* **181**, 109–122 (2018).
24. Han, F. & Mao, X. Artificial intelligence empowers enterprise innovation: evidence from china's industrial enterprises. *Appl. Econ.* **56** (57), 7971–7986 (2024).
25. Wu, Q. & Zhou, P. How does artificial intelligence change carbon emission intensity? A firm lifecycle perspective. *Applied Economics*. 1-18 (2025).
26. Nath, P. C. et al. Recent advances in artificial intelligence towards the sustainable future of agri-food industry. *Food Chemistry* **447**, 138945 (2024).
27. Chen, Y. H., Chen, C. A. & Chien, C. F. Logistics and supply chain management reorganisation via talent portfolio management to enhance human capital and resilience. *Int. J. Logistics-Research Appl.* **27** (12), 2571–2594 (2024).
28. Zhou, L. X. J., Tang, C. X. & Cao, Y. G. Innovative human capital, government support for science and technology policy, and supply chain resilience. *Finance Res. Letters* **74**, 106741 (2025).
29. De la Pen, N. & Granados, O. M. Artificial intelligence solutions to reduce information asymmetry for Colombian cocoa small-scale farmers. *Inform. Process. Agric.* **11** (3), 310–324 (2024).
30. Liu, J., Shen, H. X., Chen, J. W., Jiang, X. & Siyal, A. W. Artificial Intelligence and Carbon Emissions: Mediating Role of Energy Efficiency, Factor Market Allocation and Industrial Structure. *Energies*.18(5), (2025).
31. Wu, Y. H. Blockchain-enabled sustainable supply chain management: a study on the impact of collaboration optimization. *Management Decision*. Vol. ahead-of-print No. ahead-of-print. (2025).

32. Lin, J. B., Lin, S. Z., Benitez, J., Luo, X. & Ajamieh, A. How to build supply chain resilience: the role of fit mechanisms between digitally-driven business capability and supply chain governance. *Information & Management* **60**(2), 103747 (2023).
33. Zhang, L. P., Qiu, H. H., Chen, J. Y., Zhou, W. H. & Li, H. L. How Do Heterogeneous Networks Affect a Firm's Innovation Performance? A Research Analysis Based on Clustering and Classification. *Entropy*.25(11), (2023).
34. Sabahi, S. & Parast, M. M. Firm innovation and supply chain resilience: a dynamic capability perspective. *Int. J. Logistics-Research Appl.* **23** (3), 254–269 (2020).
35. Zhang, X., Liang, R. F. & Chen, Y. The impact of digital transformation of chain-leading enterprises on supply chain efficiency. *Supply Chain Management-an Int. J.* **30** (3), 369–382 (2025).
36. Gu, S. W. & Javed, A. Artificial Intelligence Adoption and Role of Energy Structure, Infrastructure, Financial Inclusions, and Carbon Emissions: Quantile Analysis of E-7 Nations. *Sustainability*.17(13), (2025).
37. Wu, Y., Zhu, Y. Q. & Zhao, J. F. The propulsion path of synergy and linkage based on artificial intelligence and digital economy. *Frontiers Psychology* **13**, 854542 (2022).
38. Franco, C. W., Benitez, G. B., de Sousa, P. R., Neto, F. J. K. & Frank, A. G. Managing resources for digital transformation in supply chain integration: the role of hybrid governance structures. *International J. Prod. Economics* **278**, 109428 (2024).
39. Zheng, Q., Zhao, P. T. Impacts of AI technology and government subsidy on a dual-channel fresh produce supply chain with loss-reduction. *Journal Industrial Manage Optimization*. **21** (12), 6984-7020 (2025).
40. Estep, C., Griffith, E. E. & MacKenzie, N. L. How do financial executives respond to the use of artificial intelligence in financial reporting and auditing? *Rev. Acc. Stud.* **29** (3), 2798–2831 (2024).
41. Lu, Y. & Liao, Z. F. The influence of AI application on carbon emission intensity of industrial enterprises in China. *Scientific Reports* **15**, 12585 (2025).
42. Zhang, Y. D. et al. Ecological risk assessment and response prediction caused by LUCC in the central Yunnan Province. *Scientific Reports* **15**, 2416 (2025).
43. Guo, X. G. A new comprehensive evaluation method - the combined evaluation method. *Stat. Res.* **05**, 56–59 (1995).
44. Wen, H. W., Hu, K. Y., Nghiem, X. H. & Acheampong, A. O. Urban climate adaptability and green total-factor productivity: evidence from double dual machine learning and differences-in-differences techniques. *Journal Environ. Management* **350**, 119588 (2024).
45. Guo, C. Y., Zeng, F. S. & Xia, D. P. How income inequality affects the subjective well-being of rural residents? *Frontiers Public. Health* **13**, 1496764 (2025).
46. Chen, G. R. & Yu, Z. W. Digital finance, value cocreation, and supply chain resilience: evidence from listed manufacturing firms in China. *Finance Res. Letters* **70**, 106322 (2024).
47. Guo, J. H., Chang, S. W. & Guo, M. N. The impact of peer effect of industrial robot application on enterprise carbon emission reduction. *Scientific Reports* **14**, 12070 (2024).
48. Zhang, Y. L., Zhu, J. N. & Wang, S. L. Industrial robots reduce carbon emissions in manufacturing through global value chains. *Scientific Reports* **15**, 27602 (2025).
49. He, H. H. & Zuo, Z. W. Supply chain concentration and enterprise financialization: Evidence from listed companies in China's manufacturing industry. *Plos One* **18**(5), e0285308 (2023).
50. Gao, Y. Z., Gao, H. Y., Yu, Y. J., Xu, X. F. & Chan, C. K. Green finance reform and enterprise green technology innovation-based on the perspective of Spatial spillover effect. *International Rev. Econ. & Finance* **101**, 104247 (2025).
51. Wang, Y. L., Long, Y. L. & Wang, J. Does the innovation-driven digital economy improve the resilience of industrial and supply chains? *Journal Innov. & Knowledge* **10**(3), 100733 (2025).
52. Jain, R., Li, E. P. H. & Lee, J. T. H. The role of the Indian political regime in higher education reforms for innovation drive: key comparisons with China. *J. Asian Afr. Stud.* **58** (8), 1665–1685 (2023).
53. Le, T. T. & Behl, A. Linking artificial intelligence and supply chain resilience: roles of dynamic capabilities mediator and open innovation moderator. *IEEE Trans. Eng. Manage.* **71**, 8577–8590 (2024).
54. Li, S. C. & Zhao, F. X. Research on technology innovation path of Intelligent Manufacturing enterprises-Based on qualitative comparative analysis of fuzzy sets under TOE framework. *Plos One* **19**(10), e0309784 (2024).
55. Lin, S. et al. The influence of AI on the economic growth of different regions in China. *Scientific Reports* **14**, 9169 (2024).
56. Chen, K. Y., Tao, Q. S., Wang, Y., Ding, Z. L. & Fu, R. Coupled coordination relationship and enhancement path between digital economy and essential public health services in China. *Frontiers Public. Health* **13**, 1517353 (2025).
57. Liang, X. Y., He, Q. & Jin, T. Q. Chain-Leading enterprises' artificial intelligence adoption and supply chain disruption risk. *Economics Letters* **254**, 112502 (2025).
58. Ke, Y. A., Lu, L. & Luo, X. C. Identification and formation mechanism of key elements of supply chain resilience: Exploration based on grounded theory and verification of SEM. *Plos One* **18**(11), e0293741 (2023).

Author contributions

Conceptualization, H.Z. and G.C.; methodology, H.Z.; software, H.Z.; validation, H.Z.; formal analysis, G.C.; investigation, H.Z.; resources, G.C.; data curation, H.Z.; writing—original draft preparation, H.Z.; writing—review and editing, G.C.; visualization, H.Z.; supervision, G.C.; project administration, H.Z.; funding acquisition, G.C. All authors have read and agreed to the published version of the manuscript.

Funding

Please add: This research is supported by the National Social Science Fund of China (Grant No. 22BJY150).

Declarations

Competing interests

The authors declare no competing interests.

Additional information

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1038/s41598-025-32003-z.

Correspondence and requests for materials should be addressed to G.C.