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Artificial intelligence and China–ASEAN agricultural product supply chain security: evidence from a food security perspective

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Recurrent climatic events, public-health crises, geopolitical tensions, and logistics interruptions have increased the vulnerability of international agri-food trade, making digital technology increasingly important for maintaining stable and resilient food supply systems. The empirical sample covers trade relationships between 30 Chinese provinces and 10 ASEAN economies during 2011–2023, and supply chain security is assessed from the perspectives of inward, outward, and systemic security. A multiway fixed-effects specification is used to estimate the overall influence of AI application and to identify its operating channels and conditional effects. The estimates indicate that provinces with greater industrial robot adoption generally achieve higher levels of agricultural product supply chain security. This relationship remains statistically stable under alternative treatments of extreme values, additional controls, and different clustering structures. The estimated effect is stronger in eastern provinces and in regions that initially possessed a better foundation for intelligent development. Furthermore, formal interaction tests confirm that the positive effect of AI is statistically significantly stronger in trade relationships involving less agriculture-dependent importing countries ($p = 0.007$). Logistics capacity and human capital accumulation are identified as two channels linking AI application with stronger supply chain security. Higher food consumer prices in destination markets weaken the contribution of AI, while better institutional conditions reinforce it. By focusing on agricultural trade between China and ASEAN, the analysis connects research on AI adoption with the study of cross-border supply chain security. The findings offer evidence on how emerging economies may use intelligent technologies to improve the continuity, adaptability, and reliability of agri-food supply systems.

KEYWORDS
agricultural product supply chain security, artificial intelligence application, food consumer prices, food policy, food security, food stability, food system resilience, institutional quality

1 Introduction

Building more resilient and sustainable agri-food systems is a common objective of both the United Nations 2030 Agenda and the FAO Strategic Framework 2022–2031. The Recommendations for China's 15th Five-Year Plan further call for deeper integration between trade and investment and for the rational and orderly cross-border deployment of industrial

and supply chains. Increasing international specialization has connected agricultural production, circulation, and consumption more closely across national borders. These connections generate gains from specialization, but they also allow dependence and external disturbances to spread more readily between trading economies (Awokuse et al., 2024). Because of their perishability and seasonality, agricultural products depend heavily on timely storage, transportation, and border clearance. Delays or interruptions caused by climatic, health, political, or transport-related shocks may therefore reduce food availability, damage product quality, and increase price instability (Rojas-Reyes et al., 2024; Huang et al., 2025). Maintaining secure agricultural supply chains is consequently important for food availability, livelihood protection, and the capacity of food systems to withstand shocks. Food security may also benefit from more efficient land allocation and from the effects of environmental regulation and green technological innovation. Recent evidence further suggests that rural digital transformation and smart agriculture can strengthen food security resilience by promoting technological progress and improving resource allocation (Song et al., 2026).Agricultural trade has become an increasingly important component of economic cooperation between China and ASEAN. Examining agricultural product supply chain security between China and ASEAN is therefore important not only for regional economic and trade cooperation but also for generating empirical evidence on how emerging economies can strengthen the resilience of their agri-food systems.

Despite the continued expansion of agricultural exports from Chinese provinces to ASEAN countries, the associated cross-border supply chains remain exposed to considerable systemic risks. Agricultural products traded across borders pass through a sequence of connected activities, from production and storage to transport, customs processing, and final sale. A disturbance at one stage may affect subsequent activities through delivery delays, inventory imbalances, product deterioration, and changing market prices. Supply chain vulnerability becomes greater when information is dispersed and participants cannot coordinate their decisions effectively. Fragmented information and insufficient coordination among cross-border actors may further amplify supply chain risks. Many of these problems arise because decision makers lack timely information and cannot rapidly reallocate resources when operating conditions change. AI can address part of this problem by transforming data on demand, production, inventories, storage, and transport into forecasts, warnings, and operational recommendations. In doing so, AI can reduce agricultural product losses, logistics delays, and the risk of supply chain disruption, thereby providing effective technological support for agricultural product supply chain security (El Bhilat et al., 2024; Reitano et al., 2025).

An important characteristic of the China–ASEAN agricultural trade context is that technological application and supply chain operations are organized at different geographical levels. AI application is largely determined by the technological and industrial conditions of Chinese provinces, whereas import demand, border procedures, product standards, retail structures, and institutional arrangements differ across ASEAN destination markets. Consequently, the same level of AI application may generate different supply chain outcomes across bilateral trade relationships. A forecasting or logistics system that performs effectively for one market may be less effective for another when transport distances, port conditions, inspection procedures, product composition, and demand patterns are different. The relevant analytical unit is therefore not the Chinese province or the ASEAN country considered separately, but the specific province–country trade relationship. Examining this bilateral structure helps reveal how a common technological input interacts with heterogeneous market environments. It also suggests that the contribution of AI should not be understood as automatic or uniform. Its practical value depends on whether technological information can be integrated with logistics resources, workforce capabilities, customs procedures, and the institutional conditions of the importing country. This feature makes China–ASEAN agricultural trade an appropriate setting for examining not only whether AI affects supply chain security, but also how and under what conditions this effect occurs.

Previous studies associate AI adoption with better information processing, interorganizational coordination, operating performance, and disruption management (Culot et al., 2024; Kassa et al., 2023).

Firm-level findings also suggest that digital transformation may alter both supply chain concentration and its organizational structure. Recent studies also indicate that artificial intelligence and digital technologies can strengthen supply chain resilience by enhancing continuity, adaptive capacity, and coordinated responses to disruptions (Wu et al., 2025; Sunmola and Baryannis, 2024). In the agri-food sector, related studies have largely examined specific applications, including intelligent production, distribution management, and consumer behavior. At the regional level, rural industrial upgrading has been linked to common prosperity and more sustainable agricultural development. However, the security of the complete cross-border agricultural supply chain has rarely been examined as a unified system. Evidence is also limited on the channels underlying the AI effect and on how conditions in destination markets alter its strength. Against this background, this study investigates the overall effect of AI application on agricultural product supply chain security, the mechanisms through which this effect operates, and the conditions under which it may vary, thereby clarifying the role of AI in enhancing food system resilience. Despite these valuable contributions, several gaps remain in the existing literature. First, most studies focus on general supply chains or domestic contexts, leaving the security of cross-border agricultural product supply chains largely underexplored. Second, empirical evidence on the specific mechanisms through which AI application affects this security, particularly regarding logistics capacity and human capital, remains limited. Third, the moderating roles of destination market conditions, such as food consumer prices and institutional quality, are rarely examined simultaneously. This study addresses these gaps by constructing a comprehensive analytical framework.

Existing studies have mainly measured agricultural product supply chain security using single indicators, complex network analysis, or composite indices. The single-indicator approach generally employs measures such as import dependence, trade concentration, self-sufficiency, or the stock-to-use ratio. These indicators can directly identify risks related to external dependence, source concentration, and supply security, while offering clear interpretations, straightforward calculation, and comparability across regions (Hellegers, 2022). Complex network analysis treats countries or regions as nodes and agricultural trade relationships as links. Indicators such as network centrality, connectivity, trade diversity, and shock transmission are then used to characterize the relational structure among supply chain participants and identify critical nodes and pathways of risk propagation within trade networks (Distefano et al., 2018; Jafari et al., 2024). The composite-index approach incorporates trade dependence, source diversification,

supply capacity, logistics connectivity, and risk response capacity into an integrated framework. It therefore provides a multidimensional assessment of the ability of agricultural product supply chains to withstand shocks, maintain a stable supply, and restore operations, while also offering a measurement basis for evaluating food system resilience (Tendall et al., 2015; Ritzel et al., 2024; Poo et al., 2024). Because agricultural product supply chain security encompasses risk prevention, external influence, and systemic stability, this study develops an evaluation framework consisting of three dimensions: inward security, outward security, and systemic security (Zhao and Lang, 2022; Lang and Zhao, 2024). An equal-weighting method is then used to calculate the level of agricultural product supply chain security.

AI development and application have also been quantified in several ways, including industrial robot density, composite indicator systems, AI patent applications, and total factor productivity. Industrial robot density is generally measured as the number or stock of industrial robots relative to employment and provides a direct indication of the intensity and penetration of intelligent and automated technologies in actual production processes (Acemoglu and Restrepo, 2020; Kromann et al., 2020). Composite indicator systems integrate measures of digital infrastructure, technological innovation, human capital, industrial development, and productive application, thereby capturing the overall foundations and supporting conditions for regional AI development from multiple perspectives (Ou et al., 2024). The number of AI patent applications primarily reflects knowledge production, research and development activities, and technological accumulation in the field of AI. It offers the advantages of relatively objective data, clear technological classifications, and long-term availability (Fujii and Managi, 2018; Xiao and Boschma, 2023; Gonzales, 2023). Some studies have also indirectly examined the technological progress and resource allocation effects associated with AI application through changes in total factor productivity (Luo et al., 2024). Because this study focuses on the effects of AI technologies in practical application while accounting for interprovincial differences and comparability over time, it measures provincial industrial robot density using industry-level industrial robot data published by the International Federation of Robotics and the employment shares of the corresponding industries in each province. This indicator is used as a proxy for the level of AI application.

In summary, the existing literature has mainly examined AI applications in general supply chains, manufacturing production, or individual stages of agri-food supply chains. Systematic evidence on the security of cross-border agricultural product supply chains remains limited. This study makes three principal contributions. First, it incorporates AI application into an analytical framework for cross-border agricultural product supply chain security, thereby extending the empirical context of research on the economic effects of AI. Second, using a three-dimensional province–ASEAN country–year panel, it measures agricultural product supply chain security across the dimensions of inward security, outward security, and systemic security. Third, it examines logistics capacity and human capital as transmission mechanisms and identifies the moderating effects of food consumer price levels and institutional quality in importing countries.

Accordingly, this study uses panel data covering 30 Chinese provinces and 10 ASEAN countries from 2011 to 2023 and applies a multidimensional fixed-effects model to address three questions: Does AI application improve agricultural product supply chain security? Through which mechanisms does AI exert its influence? Does its effect vary according to regional characteristics and the institutional and economic conditions of importing countries? By answering these questions, this study provides empirical evidence on how AI can enhance food system resilience and safeguard food security.

2 Theoretical analysis and research hypotheses

2.1 The effect of artificial intelligence on agricultural product supply chain security

To visually summarize the theoretical logic, Figure 1 illustrates the conceptual framework of this study. The framework posits that AI application directly enhances agricultural product supply chain security (H1). Furthermore, AI application improves supply chain security indirectly through two mediating channels: logistics capacity (H2a) and human capital accumulation (H2b). Additionally, the direct effect of AI is moderated by the food consumer price levels (H3, negative moderation) and the institutional quality of importing countries (H4, positive moderation).

Agricultural product supply chain security refers to the ability of a supply chain to maintain the continuous flow of agricultural products, withstand external shocks, and restore normal operations in a timely manner. It encompasses three core dimensions: risk prevention, external influence, and systemic stability (Tendall et al., 2015; Zhao and Lang, 2022). In the context of cross-border trade, this security is not only about domestic production capacity but also involves the coordination of international logistics, border clearance efficiency, and the stability of destination market demand.

Agricultural product supply chain security is reflected in whether product flows can be maintained, risks can be contained, and normal supply can be restored after an external disturbance. Agricultural exports from Chinese provinces to ASEAN countries involve multiple interdependent stages, including production, storage, transportation, customs clearance, and sales. The dispersion of supply chain participants and information sources increases the difficulty of demand identification, quality supervision, and cross-stage coordination.

Organizational information processing theory suggests that greater uncertainty widens the gap between the information required for coordination and the information available to decision makers (Galbraith, 1974). TAI helps narrow this gap by combining production, inventory, logistics, and market data and converting them into forecasts and operating signals. More timely and integrated information supports earlier risk detection, more accurate demand judgments, and better coordinated allocation decisions. When combined with the Internet of Things and blockchain, AI may also improve continuous product monitoring, traceability, and quality verification (Liu et al., 2025). Combining land consolidation with smart-agriculture practices may improve resource use and support food security alongside low-carbon agricultural development. The integration of AI, blockchain, and explainable decision-support systems can further improve transparency, information security, and agile responses to supply chain disruptions (Ceptureanu et al., 2025; Sadeghi et al., 2024).

Transaction cost theory further indicates that cross-border supply chains are affected by the costs of searching for information, negotiating, coordinating, monitoring, and enforcing agreements (Coase,

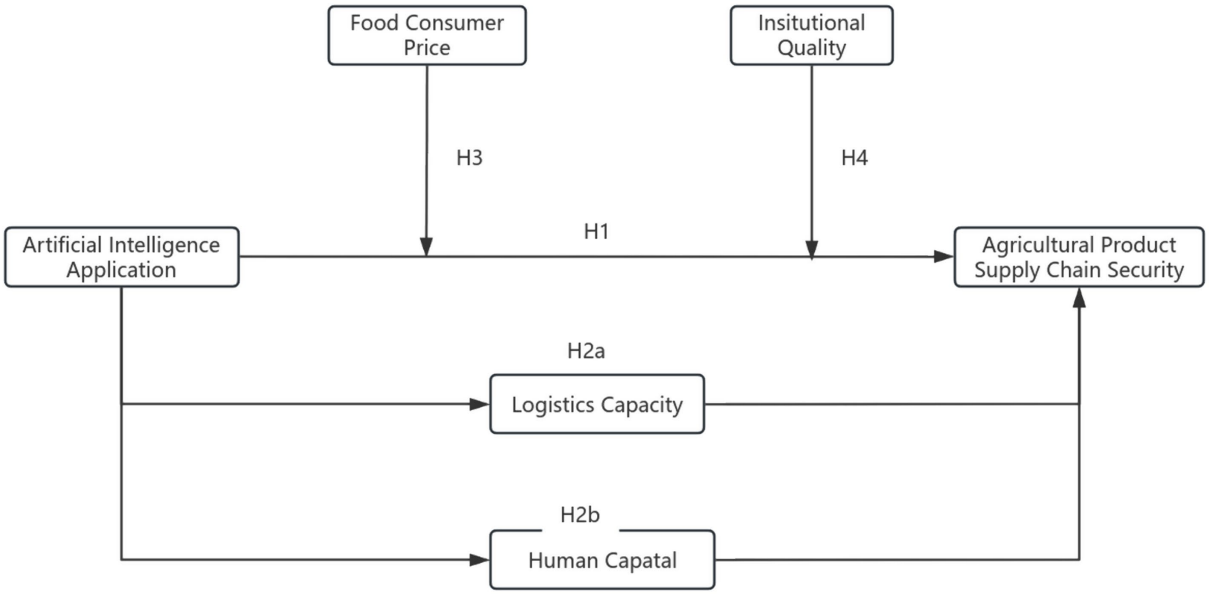

FIGURE 1
Theoretical framework of AI application and agricultural product supply chain security.

1937). Automated matching, logistics scheduling, and inventory adjustment can reduce repeated manual coordination and limit decisions based on delayed information. These applications improve the operational efficiency of storage, transportation, and distribution while reducing resource waste and supply chain coordination costs.

Earlier risk detection allows supply chain participants to intervene before a disturbance spreads and to adjust operations more quickly after disruption occurs. Firm-level evidence similarly shows that AI application can improve supply chain resilience through information transparency, dynamic capabilities, operational efficiency, and vertical spillover effects (Lin and Zhang, 2025; Yang et al., 2025). Such adjustments help limit product deterioration, imbalances between supply and demand, and prolonged interruptions in product flows. Greater agricultural product supply chain security, in turn, helps maintain a stable food supply and improve product traceability, thereby enhancing food system resilience and providing essential support for food security. Therefore, by integrating organizational information processing theory and transaction cost theory, we establish a clear logical bridge: AI application enhances information processing capacity to reduce coordination uncertainty (Galbraith, 1974), while simultaneously lowering the search and enforcement costs of cross-border transactions (Coase, 1937). These theoretical mechanisms collectively lead to more stable product flows and stronger supply chain security, which forms the theoretical basis for our first hypothesis. Based on the above analysis, this study proposes the following hypothesis:

> H_1: Artificial intelligence application significantly improves agricultural product supply chain security.

2.2 Mechanisms through which artificial intelligence affects agricultural product supply chain security

AI provides capabilities for data processing, predictive analysis, and decision support. However, technological investment does not automatically translate into improved agricultural product supply chain security. According to dynamic capabilities theory, organizations operating in rapidly changing environments must develop the ability to sense opportunities and threats, seize emerging opportunities, and reconfigure resources before general technological resources can be transformed into sustained performance advantages (Teece, 2007).

Accordingly, AI can effectively reduce cross-border supply chain risks only when it is embedded in the allocation of logistics resources and the accumulation of human capital, thereby generating corresponding operational and knowledge capabilities. This study therefore examines logistics capacity and human capital as two mechanisms through which AI affects agricultural product supply chain security.

2.2.1 Logistics capacity

One channel through which AI may strengthen supply chain security is the improvement of logistics capacity. Organizational information processing theory suggests that greater environmental uncertainty increases an organization's demand for information processing. When information-processing capacity is insufficient to meet decision-making requirements, judgment errors, coordination delays, and resource misallocation are more likely to occur.

Cross-border agricultural product supply chains involve multiple participants across production, storage, transportation, customs clearance, and sales. Information concerning market demand, inventory conditions, transportation capacity, and external risks is therefore dispersed across different stages. Because agricultural products are perishable and highly sensitive to transportation time, delayed information transmission or inappropriate logistics decisions can rapidly result in product spoilage, transportation delays, and supply disruptions.

By jointly analysing orders, stocks, transport availability, traffic, weather, and market demand, AI gives logistics operators a broader basis for allocation decisions. It can thus improve demand forecasting

and anomaly detection and expand the information-processing capacity of the supply chain (Toorajipour et al., 2021). Explainable AI-based demand forecasting can also reduce forecasting errors and strengthen the resilience of perishable product supply chains (Jauhar et al., 2025). However, according to dynamic capabilities theory, informational advantages can improve supply chain operations only when they are further transformed into capabilities for resource reconfiguration.

AI-generated forecasts and warnings can be translated into changes in routes, vehicle allocation, warehouse use, and delivery schedules. These functions enable logistics participants to reallocate transportation and storage resources promptly in response to environmental changes. These adjustments reduce unused transport capacity, excessive inventory, and repeated handling while making logistics operations more observable and adaptable. Existing studies have shown that AI can improve agri-food supply chain performance by increasing the efficiency of distribution networks (El Bhilat et al., 2024).

Stronger logistics capacity supports supply chain security through both efficiency improvements and operational substitution. First, greater transportation capacity and logistics efficiency shorten the time agricultural products remain in storage, transit, and border clearance, thereby reducing the risks of spoilage, delay, and supply–demand mismatch. Second, when existing transportation routes or logistics nodes are disrupted, stronger logistics coordination capacity facilitates the reallocation of transportation resources and the selection of alternative routes, preventing localized shocks from spreading throughout the supply chain.

AI therefore improves information-processing capacity, promotes the optimal allocation of logistics resources, and ultimately strengthens the ability of agricultural product supply chains to maintain stable operations and restore supply. Despite the theoretical recognition of logistics in supply chains, empirical evidence directly testing the mediating role of logistics capacity in the relationship between AI application and cross-border agricultural supply chain security remains scarce. Most studies focus on firm-level distribution efficiency, lacking macro-level cross-border empirical verification. This study fills this gap by empirically testing this mechanism.

Accordingly, this study proposes the following hypothesis:

> H_2a: Artificial intelligence application improves agricultural product supply chain security by enhancing logistics capacity.

2.2.2 Human capital accumulation

Human capital provides a second mechanism linking AI application with supply chain security. Human capital theory regards education, training, and knowledge acquisition as investments that raise workers' productive abilities. When the expected returns to a particular set of skills increase, individuals and organizations have stronger incentives to invest in the corresponding human capital (Becker, 1962).

AI application transforms conventional modes of production and management and increases demand for compound skills involving digital technology, data analysis, risk management, and interorganizational coordination. Previous research has shown that demand for AI-related skills is increasing across industries and occupations and that these skills are complementary to cognitive, software, and managerial capabilities (Alekseeva et al., 2021). Such complementarity between technology and skills increases the market returns to relevant forms of human capital, thereby encouraging workers to undertake education and skills training and motivating firms and regions to increase investment in talent development and knowledge accumulation (Bresnahan et al., 2002).

The role of human capital in linking AI to agricultural product supply chain security can also be explained by absorptive capacity theory. This theory argues that an organization's existing knowledge base determines its ability to recognize, assimilate, and apply external knowledge (Cohen and Levinthal, 1990). Demand forecasts, risk warnings, and resource allocation recommendations generated by AI cannot automatically be converted into supply chain decisions. Their effective implementation requires skilled workers to interpret, evaluate, and apply these outputs in light of agricultural product characteristics, trade regulations, technical standards, and conditions in importing markets.

A higher level of human capital improves the ability of supply chain participants to learn and use AI technologies. It reduces model misinterpretation, technological misuse, and the disconnection between technical systems and business practices. It also facilitates communication and coordination among exporters, logistics enterprises, customs and border authorities, and importers. Furthermore, employees equipped with digital skills and supply chain management knowledge can identify market changes and potential risks more accurately and adjust production, inventory, and logistics arrangements promptly in response to AI-generated information. These capabilities improve supply chain visibility, responsiveness, and flexibility (Nikookar and Yanadori, 2022).

By increasing the value of digital, analytical, and managerial skills, AI creates stronger incentives for workers, firms, and regions to invest in relevant knowledge and training. Human capital, in turn, converts the informational advantages generated by AI into risk-response capabilities by strengthening technological absorption, information interpretation, and organizational coordination. This process ultimately improves agricultural product supply chain security. Although the importance of human capital in technology adoption is well established, its mediating role in the context of AI-driven cross-border agricultural supply chain security lacks rigorous empirical testing. Existing literature mainly focuses on domestic labor markets or general firm innovation, overlooking how AI-induced human capital accumulation translates into supply chain risk resilience across borders.

Accordingly, this study proposes the following hypothesis:

> H_2b: Artificial intelligence application improves agricultural product supply chain security by promoting human capital accumulation.

2.3 The moderating effect of consumer food price levels in importing countries

The usefulness of AI-based decisions depends partly on whether available information-processing capacity is sufficient for the uncertainty faced by supply chain participants. When the external

environment is relatively stable, firms can use historical data and AI technologies to improve the accuracy of demand forecasting, inventory allocation, and logistics scheduling. When substantial market changes sharply increase information-processing requirements, however, the enabling effect of technology may be constrained. The effect of AI on agricultural product supply chain security may therefore depend on the consumer market environment of the importing country.

Rising food prices first affect the purchasing power and consumption choices of final consumers. Higher food prices reduce consumers' real purchasing power and encourage them to adjust purchase quantities, product categories, and sourcing choices. These effects are particularly pronounced among lower-income households and in lower-income economies (Green et al., 2013). Changes in demand structure and purchasing patterns reduce the representativeness of historical data for future market conditions and may shift the price–demand relationships identified by AI systems. Because the effectiveness of AI-based forecasting depends on the continuity and reliability of data, frequent market fluctuations may reduce both forecasting accuracy and firms' willingness to rely on algorithmic recommendations (Scarton et al., 2026).

Price changes may also enlarge demand fluctuations as revised orders move from retailers to importers and exporters. The bullwhip effect suggests that changes in final demand can become increasingly amplified as they are transmitted from retailers to importers and exporters, with price fluctuations and forecast revisions serving as important contributing factors (Lee et al., 1997). Rising consumer prices may prompt importers and retailers to adjust orders, selling prices, and inventory levels more frequently. Decisions made by different participants on the basis of localized information may therefore cause trade orders to deviate from actual market demand, resulting in either excess inventory or supply shortages and weakening the resource allocation benefits of AI.

Finally, transaction cost theory suggests that environmental uncertainty increases the costs of information search, contract negotiation, monitoring, and enforcement (Williamson, 1979). Higher consumer prices also increase the financial pressures associated with procurement, storage, transportation, and working capital. Importers may consequently shorten contract durations, reduce inventory holdings, or adopt more cautious purchasing strategies. Inflation can further alter firms' ordering, supply, and pricing decisions and thereby increase the difficulty of supply chain coordination (Akhavan Chayjan et al., 2025).

Overall, higher food prices make demand signals less reliable, encourage more frequent order revisions, and raise coordination costs, thereby reducing the security benefits generated by AI. While existing literature has extensively examined the macro-impacts of food price volatility on trade and welfare, its moderating effect on the efficacy of AI applications in cross-border supply chains remains underexplored. It is unclear whether high food prices in destination markets hinder the operationalization of AI-driven forecasts. This study addresses this gap by investigating the moderating role of food consumer price levels. Accordingly, this study proposes the following hypothesis:

> H_3: Consumer food price levels in importing countries negatively moderate the effect of artificial intelligence application on agricultural product supply chain security.

2.4 The moderating effect of institutional quality in importing countries

New institutional economics argues that institutions reduce market uncertainty and transaction costs by defining property rights, regulating transaction behavior, and providing mechanisms for contract enforcement (Williamson, 2000). The enabling effect of AI on cross-border agricultural product supply chain security does not arise in an institutional vacuum. Whether AI-based demand forecasting, quality traceability, and risk early-warning systems can be translated into actual performance depends on the rule of law, regulatory quality, and government effectiveness of the importing country. Institutional quality therefore constitutes an important boundary condition for the effectiveness of AI application.

First, Predictable policies and transparent regulation reduce compliance uncertainty and make long-term digital investment less risky for firms. Importing countries characterized by policy stability, regulatory transparency, and high administrative efficiency reduce firms' concerns regarding regulatory changes and compliance risks. Exporters, logistics enterprises, and importers are consequently more willing to establish long-term digital cooperation. By contrast, institutional deficiencies and regulatory uncertainty may impede the integration of digital technologies with supply chain management (Domingues et al., 2026).

Second, Reliable contract enforcement and greater transaction trust also reduce the risks associated with sharing commercial and operational information. Cross-border agricultural trade involves incomplete contracts concerning quality standards, delivery schedules, cold-chain responsibilities, and payment settlement. Stronger property-rights protection and judicial enforcement reduce opportunistic behavior and contractual default, thereby increasing the willingness of supply chain participants to share data on orders, inventories, logistics, and product quality. Transaction insecurity acts as an implicit tax that suppresses trade (Anderson and Marcouiller, 2002), whereas stronger institutional quality and institutional similarity promote bilateral trade (De Groot et al., 2004). Contract enforcement and trust are also complementary, and improvements in both produce greater gains in trade cooperation efficiency (Bartling et al., 2025). Under such conditions, the data required by AI systems are more continuous and reliable, and AI-generated predictions are more likely to be translated into coordinated decisions.

Finally, government effectiveness and regulatory quality improve the efficiency with which the informational advantages of AI are converted into supply chain resilience. An effective government can standardize customs procedures, coordinate technical standards, and promote data sharing across public agencies, thereby reducing administrative delays and institutional costs. Effective government support can strengthen digital adaptability and digital agility, which in turn improve supply chain resilience (Dubey et al., 2023). Institutional and infrastructure quality also influence market access and bilateral trade performance (Francois and Manchin, 2013).

Therefore, the higher the institutional quality of the importing country, the more effectively AI can be embedded in business processes and converted into supply chain stability and recovery capacity. Although institutional quality is widely recognized as a facilitator of trade, its boundary condition role in moderating the relationship between AI application and cross-border agricultural supply chain security requires further investigation. Most studies focus on the

direct impact of institutions on trade flows, ignoring how they shape the returns of digital technologies. This study fills this gap by examining how institutional quality moderates this relationship. Accordingly, this study proposes the following hypothesis:

> H_4: Institutional quality in importing countries positively moderates the effect of artificial intelligence application on agricultural product supply chain security.

3 Research design

3.1 Model specification and data sources

3.1.1 Model specification

The empirical model relates provincial AI application to the security of agricultural export supply chains connecting China with ASEAN markets. The following baseline econometric model is specified:

$$\text{security}_{ict} = \alpha + \beta AI_{it} + \gamma \text{Controls}_{ict} + \mu_i + \lambda_j + \sigma_t + \varepsilon_{ijt} \quad (1)$$

where i denotes a Chinese province, j denotes an ASEAN country, and t denotes the year. security_{ict} is the dependent variable and represents the composite security index of the agricultural product export supply chain between Chinese province i and ASEAN country j in year t. AI_{it} is the core explanatory variable, representing the level of AI application in province in year t. It is measured using the estimated scale of industrial robot adoption at the provincial level and is transformed using the natural logarithm. Controls_{ict} denotes a set of country-level control variables. In addition, λ_j, σ_t, ε_{ijt} represent province, ASEAN-country, and year fixed effects, respectively, while ε_{ijt} is the random error term.

Following the multiway fixed-effects specification (Guimarães and Portugal, 2010), the estimation jointly absorbs province, ASEAN-country, and year fixed effects. This approach controls for unobserved characteristics associated with each of the three panel dimensions (Guimarães and Portugal, 2010). Because the level of AI application in a given Chinese province varies jointly across observations involving different ASEAN countries, standard errors are clustered at the provincial level to account for potential heteroskedasticity and within-cluster error correlation (Cameron and Miller, 2015).

3.1.2 Data sources

The empirical database combines information from multiple authoritative sources. Trade data are obtained from the UN Comtrade Database. Macroeconomic and institutional indicators are sourced from the World Bank World Development Indicators (WDI) database. Data on agricultural production, employment, and regional characteristics are collected from the National Bureau of Statistics of China, specifically the China Statistical Yearbook, the China Labour Statistical Yearbook, and provincial statistical yearbooks. Data on artificial intelligence application are derived from the International Federation of Robotics (IFR) database and the China Labour Statistical Yearbook. Other firm-level or supplementary data are obtained from the Chinese Research Data Services Platform (CNRDS). Because some indicators in these databases were no longer consistently updated after 2023, the study period is restricted to 2011–2023.

3.2 Variable definition and measurement results

3.2.1 Dependent variable

The dependent variable is the security level of agricultural product export supply chains from China to ASEAN countries. Drawing on the three-dimensional supply chain security framework, this study constructs an evaluation system comprising three primary dimensions—namely, inward security, outward security, and systemic security—as well as seven secondary indicators and 12 tertiary indicators.

Index construction begins by reversing the direction of negative indicators and then applying min–max normalization to place all variables on a comparable scale. The 12 tertiary indicators are then assigned equal weights, and the composite agricultural product supply chain security index is calculated using the arithmetic mean. Accordingly, each tertiary indicator receives a weight of (1/12).

The data used to construct the index are obtained from the UN Comtrade Database, the National Bureau of Statistics of China, and relevant statistical yearbooks. The final sample covers agricultural trade between 30 Chinese provinces and 10 ASEAN countries from 2011 to 2023, yielding a balanced panel of 3,900 observations (Table 1).

As shown in Table 2, the mean value of the composite supply chain security index is 0.471, with a standard deviation of 0.089. The index ranges from 0.203 to 0.747, indicating substantial variation in supply chain security across Chinese provinces and ASEAN partner countries. This uneven pattern may reflect marked differences in

TABLE 1 Indicator system for agricultural product supply chain security.

Primary dimension	Secondary dimension	Tertiary indicator
Inward security	Import side	Import dependence
		Import Herfindahl–Hirschman index
	Export side	Export concentration
		Export Herfindahl–Hirschman index
	Domestic capacity	Agricultural value added
		Total power of agricultural machinery
		Road mileage
		Internet penetration rate
Outside security	Market influence	Market share
	Competitiveness	Trade competitiveness
Systemic security	Network structure	Number of agricultural trade links
	Stability	Export product diversity

TABLE 2 Descriptive statistics of the composite supply chain security index.

Observations	Mean	Standard deviation	Minimum	Maximum
3900	0.4712	0.0887	0.2028	0.7469

logistics infrastructure, cold-chain coverage, and customs-clearance efficiency among Chinese provinces, together with variation in institutional quality and inspection and quarantine standards across ASEAN countries.

Figure 1 presents the overall trend in the security of agricultural product export supply chains from China to ASEAN countries between 2011 and 2023. The index exhibits a fluctuating but generally upward trajectory, increasing from 0.366 in 2011 to 0.494 in 2023, which represents an overall increase of approximately 35%. More specifically, the period from 2011 to 2014 was characterized by rapid improvement, with the index rising from 0.366 to a peak of 0.533, equivalent to an average annual growth rate of approximately 13.4%. In 2015, the index declined to 0.463 amid developments in the South China Sea and changes in the external trade environment. It subsequently fluctuated between approximately 0.45 and 0.51 during 2016–2020. In 2021, the index fell to a temporary low of 0.424 following the shock of the COVID-19 pandemic. With the entry into force of the Regional Comprehensive Economic Partnership Agreement and the post-pandemic recovery of supply chains, the index rebounded to 0.494 in 2023.

Overall, the security of China–ASEAN agricultural product export supply chains improved during the sample period. Nevertheless, the year-to-year fluctuations caused by external shocks indicate that the resilience of these supply chains requires further strengthening (Figure 2).

Figure 3 reports differences in average supply chain security scores across Chinese provinces. Shandong records the highest average score at 0.634, followed by Henan at 0.583, Sichuan at 0.553, Jiangsu at 0.551, and Hebei at 0.544. These provinces are either major agricultural producers or economically developed regions and generally possess strong agricultural export competitiveness.

By contrast, Qinghai records the lowest average score at 0.318, followed by Ningxia at 0.348, Hainan at 0.380, Tianjin at 0.390, and Beijing at 0.392. These lower-ranking regions mainly include geographically remote western provinces or provincial-level municipalities with relatively limited agricultural production capacity. The provincial ranking is broadly consistent with differences in agricultural resource endowments, economic foundations, and geographical locations, highlighting the uneven regional distribution of agricultural product supply chain security.

3.2.2 Core explanatory variable

The core explanatory variable is the level of AI application. Industrial robots constitute an important channel through which AI and automation technologies are embedded in physical production processes. The scale of industrial robot adoption therefore provides a relatively direct measure of the actual application and penetration of intelligent technologies in regional production activities.

Following the measurement methods adopted by Kang and Lin (2021) and Lu and Meng (2021), provincial industrial robot adoption is estimated in three steps. First, the industry classifications used by the International Federation of Robotics (IFR) are matched with the disaggregated manufacturing industries reported in the China Labour Statistical Yearbook. Second, for each industry, the share of employment in each province relative to national employment in the same industry is calculated. Third, the national number of newly installed industrial robots in each industry is allocated across provinces using these employment shares as weights. The estimated values are then aggregated across industries to obtain the scale of industrial robot adoption in each province.

Related studies have similarly combined industry-level robot data from the IFR with regional industrial employment structures to construct regional indicators of robot adoption or robot exposure (Shen and Zhang, 2024; Luo et al., 2025).

Overall, the operational stock of industrial robots in China increased from 74,000 units in 2011 to 1.755 million units in 2023, representing an average annual growth rate of 29.8% and a cumulative increase of approximately 22.6 times. Annual installations increased from 23,000 units in 2011 to 156,000 units in 2017. They subsequently remained at a high level, reaching 275,000 units in 2021 and 290,000 units in 2022, before declining slightly to 276,000 units in 2023. Since 2013, China has remained the world's largest industrial robot market for 11 consecutive years (Figure 4).

3.2.3 Control and moderating variables

This study includes the following control variables: the population size of each ASEAN country ((pop)), political stability ((stab)), exchange-rate volatility ((fx)), and GDP per capita ((gdp_percap)). The food consumer price indicator of each ASEAN country ((cpi)) is used in the moderating-effect analysis. Table 3 presents the descriptive statistics for the dependent variable, the core explanatory variable, the control variables, and the food consumer price variable.

4 Empirical analysis

4.1 Baseline regression results

Before estimating the baseline relationship, the Hausman test is used to select between fixed- and random-effects specifications. The test yields a value of (Prob > chi2 = 0.0000) rejecting the null hypothesis and indicating that the fixed-effects model is preferable to the random-effects model. The baseline model is subsequently estimated using the multiway fixed-effects approach.

The first specification in Table 4 includes only the core explanatory variable and the fixed effects. The coefficient of AI application is 0.0096 and is statistically significant at the 5% level, indicating that

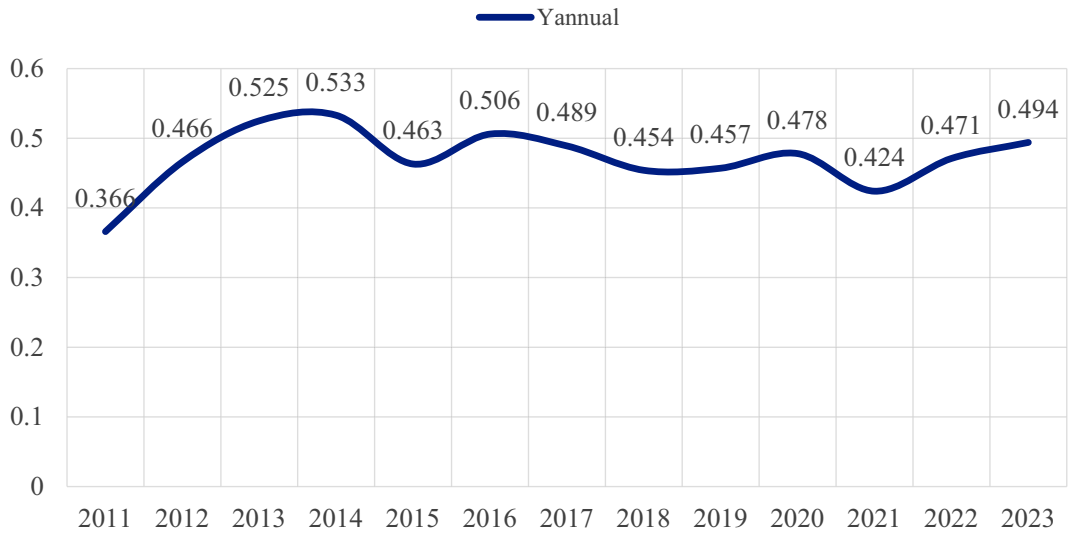

FIGURE 2
Smoothed overall trend in the security of agricultural product export supply chains from China to ASEAN countries, 2011-2023.

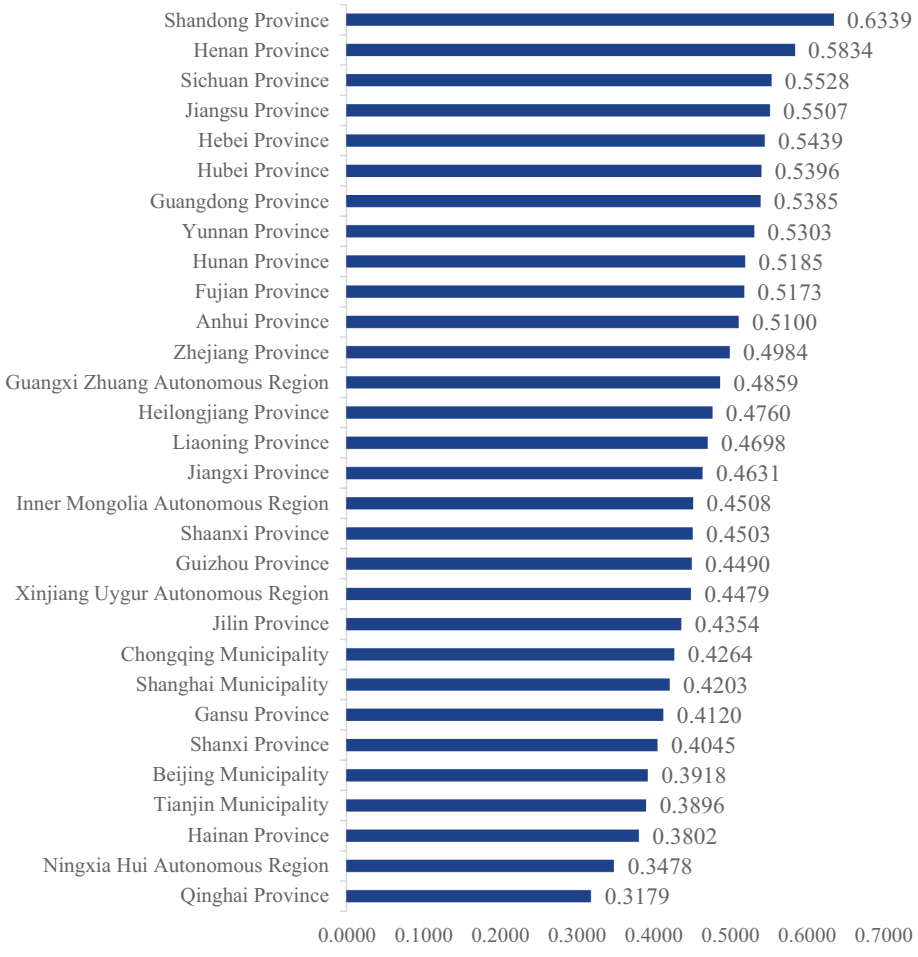

FIGURE 3
Ranking of average agricultural product supply chain security scores across Chinese provinces.

AI application has a significant positive effect on agricultural product supply chain security.

Population, political stability, exchange-rate volatility, GDP per capita, and food consumer prices are added successively in Columns (2)–(6). The coefficient of AI application remains approximately 0.0096 in all specifications and is consistently significant at the 5% level. Neither the size nor the significance of the AI estimate changes materially as the control set is expanded. These results indicate that

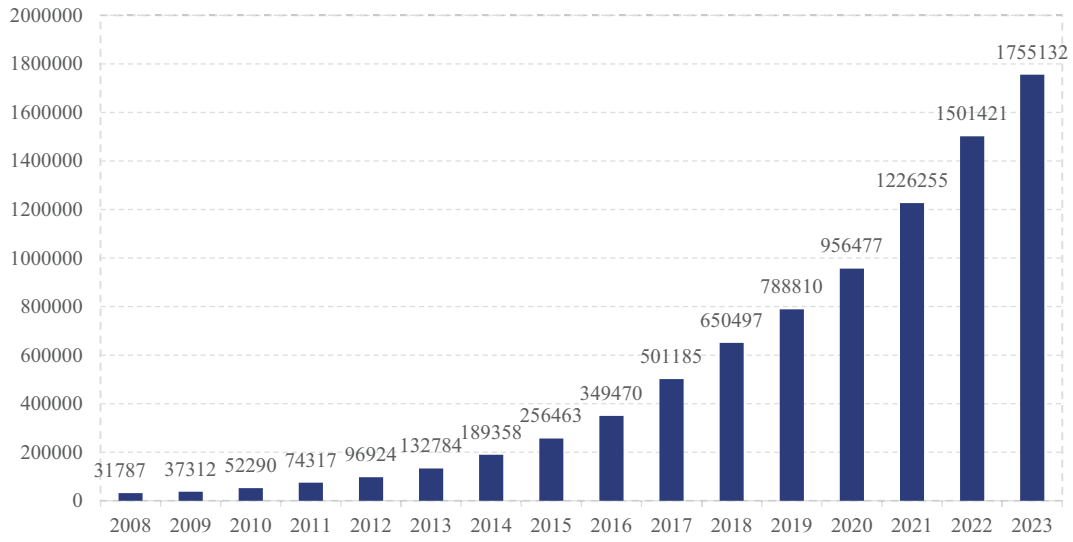

FIGURE 4
Operational stock of industrial robots in China, 2008–2023.

TABLE 3 Descriptive statistics of the main variables.

Variable	Observations	Mean	Standard deviation	Minimum	Maximum
Agricultural product supply chain security	3,900	0.4712	0.0887	0.2028	0.7469
Artificial intelligence application	3,870	8.5726	1.5597	4.7123	12.4331
Population of ASEAN countries	3,900	65,288,888	76,230,000	399,389	281,000,000
Political stability of ASEAN countries	3,900	−0.1293	0.8705	−2.2413	1.3860
Exchange-rate volatility of ASEAN countries	3,810	0.0600	0.4245	−0.0943	4.7680
GDP per capita of ASEAN countries	3,900	14,412.66	21,836.49	959.15	92,148.3
Food consumer price indicator of ASEAN countries	3,900	4.5557	4.8194	−1.0796	37.9977

a higher level of AI application significantly improves the security of agricultural product export supply chains from China to ASEAN countries and that this conclusion is not sensitive to the selection of control variables.

This finding is broadly consistent with Zhang and Zhang (2026), who also show that AI can significantly improve supply chain stability. AI may enhance the security of China–ASEAN agricultural product export supply chains by reducing information-search and coordination costs in cross-border trade and improving the efficiency of cold-chain logistics scheduling and quality traceability. The result is also consistent with Tang et al. (2025), who find that AI strengthens supply chain resilience during the preparedness, response, and recovery stages by reducing supply chain dependence and improving continuity and operational efficiency.

After all control variables are included in Column (6), the estimated coefficient of AI application remains 0.0096 and is significant at the 5% level. Hypothesis H_1 is therefore supported.

4.2 Robustness checks

Table 5 reports four sensitivity tests: winsorizing AI application, winsorizing the dependent variable, adding institutional quality, and clustering standard errors by ASEAN country and excluding the COVID-19 shock year (2020). In every specification, the coefficient on AI application remains positive and statistically significant. The baseline result is therefore not driven by extreme observations, the additional institutional control, or the selected clustering level or the COVID-19 shock.

TABLE 4 Baseline regression results.

	(1)	(2)	(3)	(4)	(5)	(6)
ln_ai	0.0096**	0.0096**	0.0096**	0.0096**	0.0096**	0.0096**
	(0.0043)	(0.0043)	(0.0043)	(0.0043)	(0.0043)	(0.0043)
ln_pop		−0.0553**	−0.0504**	−0.0437*	−0.0475**	−0.0437*
		(0.0228)	(0.0226)	(0.0227)	(0.0228)	(0.0227)
Stab			−0.0037**	−0.0026	−0.0035*	−0.0034*
			(0.0017)	(0.0017)	(0.0018)	(0.0018)
fx				−0.0021**	−0.0021**	−0.0021**
				(0.0009)	(0.0009)	(0.0009)
ln_gdp					0.0046**	0.0042**
					(0.0019)	(0.0019)
cpi						−0.0013
						(0.0011)
_cons	0.3884***	1.3302***	1.2454***	1.1317***	1.1567***	1.0969***
	(0.0371)	(0.3789)	(0.3755)	(0.3771)	(0.3770)	(0.3757)
N	3,870	3,870	3,870	3,870	3,870	3,870
Province FE	Yes	Yes	Yes	Yes	Yes	Yes
ASEAN FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.9272	0.9273	0.9274	0.9274	0.9274	0.9274

Province-clustered robust standard errors are reported in parentheses. All specifications include province, ASEAN-country, and year fixed effects. (*$p < 0.10$), (**$p < 0.05$), and (***$p < 0.01$).

4.3 Heterogeneity analysis

Table 6 compares the effect of AI application across geographical location, initial AI development, and the agricultural dependence of ASEAN partner countries.

4.3.1 Heterogeneity by geographical location

The coefficient of AI application is 0.0093 and significant at the 5% level for eastern provinces, whereas the estimate of 0.0079 for non-eastern provinces is insignificant. The effect is therefore concentrated mainly in eastern China.

A possible explanation is that the practical effect of AI depends not only on technological investment but also on complementary conditions, including digital infrastructure, skilled labor, industrial foundations, and logistics networks. Forman et al. (2012) find that the economic benefits of advanced internet technologies are concentrated in regions with higher initial levels of economic development, stronger educational foundations, and greater concentrations of information technology industries. This finding indicates that the effects of digital technologies are highly dependent on regional conditions.

Transport infrastructure also improves market accessibility and factor mobility, thereby providing the physical conditions required for new technologies to be embedded in interregional production and distribution activities (Banerjee et al., 2020). Compared with other regions, eastern China possesses stronger digital infrastructure, more developed logistics networks, a larger pool of skilled workers, and more complete industrial support systems. These complementary advantages enable eastern provinces to convert AI application more effectively into risk identification, logistics coordination, and emergency-response capabilities in cross-border agricultural product supply chains. Recent evidence likewise indicates that the resilience and security effects of intelligent technologies are stronger when firms possess better internal capabilities, external linkages, and regional digital infrastructure (Wang et al., 2026; Yu et al., 2026). To rigorously test the regional difference, we introduced an interaction term between AI application and the eastern region dummy. The interaction term is statistically significant (coefficient = −0.0069, $p = 0.022$), formally confirming that the positive effect of AI is significantly stronger in eastern provinces.

4.3.2 Heterogeneity by initial AI foundation

The estimate is 0.0120 and significant at the 1% level in provinces with a stronger initial AI foundation. By contrast, the coefficient falls to 0.0029 and becomes insignificant in the low-initial-AI group.

In this study, provinces are divided into high and low initial AI foundation groups based on the median value of the AI application indicator in the initial year (2011) of the sample period. Technological diffusion does not occur simultaneously or with equal intensity across regions. The speed and depth of technology adoption depend jointly on the existing equipment base, accumulated knowledge, skilled labor, and the regional industrial ecosystem. Comin and Hobijn (2010) find substantial differences in the speed of technology adoption across countries and technologies and show that such differences explain a considerable share of variation in economic performance. Comin and Mestieri (2018) further argue that even after a technology has entered

TABLE 5 Robustness check results.

	(1)	(2)	(3)	(4)	(5)
ln_ai		0.0110**	0.0096**	0.0096***	0.0096**
		(0.0044)	(0.0043)	(0.0013)	(0.0046)
ln_pop	−0.0437*	−0.0457**	−0.0480**	−0.0437	−0.0393*
	(0.0227)	(0.0220)	(0.0229)	(0.0469)	(0.0228)
Stab	−0.0034*	−0.0032*	−0.0076***	−0.0034	−0.0032*
	(0.0018)	(0.0017)	(0.0022)	(0.0020)	(0.0018)
fx	−0.0021**	−0.0022**	−0.0011	−0.0021***	−0.0019**
	(0.0009)	(0.0009)	(0.0008)	(0.0003)	(0.0009)
ln_gdp	0.0042**	0.0042**	0.0027	0.0042	0.0038*
	(0.0019)	(0.0018)	(0.0019)	(0.0055)	(0.0020)
cpi_10	−0.0013	−0.0014	−0.0006	−0.0013	−0.0009
	(0.0011)	(0.0010)	(0.0011)	(0.0015)	(0.0011)
ln_ai_w	0.0100**				
	(0.0043)				
inst			0.0164***		
			(0.0048)		
Constant	1.0939***	1.1194***	1.1834***	1.0969	1.0252**
	(0.3763)	(0.3657)	(0.3804)	(0.7892)	(0.3779)
N	3,870	3,870	3,870	3,870	3,570
Province FE	Yes	Yes	Yes	Yes	Yes
ASEAN FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
R^2	0.9275	0.9240	0.9276	0.9274	0.9286

Cluster-robust standard errors are reported in parentheses. Columns (1)–(3) cluster standard errors at the Chinese province level, whereas Column (4) clusters them at the ASEAN-country level. (*$p < 0.10$), (**$p < 0.05$), and (***$p < 0.01$).

different economies, its intensity of use may continue to differ substantially, resulting in heterogeneous productivity effects.

Regions with a stronger initial AI foundation have already accumulated advantages in equipment, talent, knowledge, and industrial support. These advantages reduce the adjustment costs involved in integrating subsequent AI applications with supply chain operations and allow the security-enhancing effects of AI to be more fully realized. Regional AI development can also strengthen firms' supply chain resistance and recovery capacity by improving supply–demand matching and enhancing supply quality (Ma et al., 2025). Although the coefficient for the high-initial-AI group is larger (0.0120 vs. 0.0029), the formal interaction term test reveals that the difference between the two groups is not statistically significant ($p = 0.255$). Therefore, we interpret this stronger effect in high-AI regions as suggestive evidence rather than a definitive subgroup difference.

4.3.3 Heterogeneity by agricultural dependence

AI application has a positive effect in both agricultural-dependence groups. However, the coefficient-difference test shows that the effect is significantly stronger for trade relationships involving less agriculture-dependent ASEAN countries ($p = 0.007$).

Trade relationships are classified into high and low agricultural dependence groups based on the median share of agricultural value added in GDP for ASEAN countries over the sample period. This result suggests that AI application produces a stronger improvement in agricultural product supply chain security when the importing country has a lower degree of agricultural dependence. The share of agricultural value added in GDP reflects not only the relative importance of agriculture in the national economy but also, to some extent, the degree of structural transformation. Structural transformation generally involves the reallocation of labor and other resources from agriculture toward industry and services and is closely related to changes in sectoral and aggregate productivity (Duarte and Restuccia, 2010).

A lower degree of agricultural dependence does not necessarily imply weaker demand for agricultural products. Instead, it may indicate that the importing country has a more diversified economic structure, more developed digital infrastructure, and stronger technological absorptive capacity. These conditions provide a more favorable environment for applying AI to customs clearance, logistics, traceability, and cross-organizational supply chain coordination. This interpretation is based on the characteristics of the sample used in this study and does not equate agricultural dependence directly with the level of economic development. The formal coefficient-difference test yields a p-value of 0.007, statistically confirming that the positive effect of AI is significantly stronger in trade relationships involving less agriculture-dependent ASEAN countries. Although the absolute coefficient for the high-dependence group (0.0102) is larger, the interaction term (−0.0035, $p = 0.007$) confirms the low-dependence group exhibits a statistically more robust effect.

TABLE 6 Heterogeneity analysis.

	Eastern region	Non-eastern region	High initial AI level	Low initial AI level	High agricultural dependence	Low agricultural dependence
ln_ai	0.0093**	0.0079	0.0120***	0.0029	0.0102*	0.0090**
	(0.0035)	(0.0072)	(0.0038)	(0.0082)	(0.0052)	(0.0036)
ln_pop	−0.0001	−0.0690**	0.0038	−0.0913**	−0.3971***	0.0441*
	(0.0356)	(0.0284)	(0.0278)	(0.0321)	(0.1155)	(0.0242)
Stab	−0.0049	−0.0026	−0.0030	−0.0039	−0.0040	0.0026
	(0.0028)	(0.0023)	(0.0022)	(0.0028)	(0.0041)	(0.0031)
fx	−0.0009	−0.0028**	−0.0013	−0.0030*	−0.0018*	0.0284**
	(0.0011)	(0.0013)	(0.0011)	(0.0014)	(0.0009)	(0.0134)
ln_gdp	−0.0001	0.0067**	0.0025	0.0060*	0.0283***	0.0106**
	(0.0023)	(0.0026)	(0.0022)	(0.0031)	(0.0063)	(0.0043)
cpi	−0.0012	−0.0014	−0.0029***	0.0005	0.0003	−0.0082**
	(0.0019)	(0.0013)	(0.0010)	(0.0018)	(0.0012)	(0.0033)
_cons	0.4016	1.5157***	0.3060	1.9157***	7.1396***	−0.4279
	(0.5972)	(0.4821)	(0.4583)	(0.5300)	(2.0030)	(0.4089)
N	1,420	2,450	1,940	1,930	1,935	1,935
Province FE	Yes	Yes	Yes	Yes	Yes	Yes
ASEAN FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.9583	0.9173	0.9465	0.9013	0.9255	0.9374

Province-clustered robust standard errors are reported in parentheses. (*$p < 0.10$), (**$p < 0.05$), and (***$p < 0.01$). The p-values for coefficient differences are 0.022 for geography, 0.255 for initial AI foundation, and 0.007 for agricultural dependence.

4.4 Endogeneity test

To address potential endogeneity concerns, we employ an instrumental variable (IV-2SLS) approach using the one-period and two-period lagged AI application (L.ln_ai and L2.ln_ai) as instruments. The results are reported in Table 7. The first-stage F-statistic is 39.95, far exceeding the conventional threshold of 10, confirming the relevance of our instruments. The Hansen J test ($p = 0.5873$) confirms their validity. The second-stage results show that the coefficient of AI application remains positive and statistically significant ($\beta = 0.0188$, $p = 0.034$), consistent with our baseline findings. Notably, the endogeneity test ($p = 0.3668$) fails to reject the null hypothesis that AI application is exogenous, indicating that our baseline estimates are not severely biased. Second, to evaluate the potential impact of omitted variable bias, we conduct the Oster (2019) test. The results yield a delta value of 1.000, indicating that unobserved factors would need to be as strong as all observed control variables combined to nullify the AI effect. Considering the negligible R-squared difference (0.9285 vs. 0.9282) between the controlled and restricted models, such a scenario is highly unlikely. Overall, the endogeneity tests confirm the robustness of our conclusions.

5 Mechanism and moderation analyses

5.1 Mechanism analysis

The mechanism analysis first confirms the overall AI effect and then examines whether AI application is associated with the proposed intermediate variables. First, agricultural product supply chain security is used as the dependent variable to estimate the overall effect of AI application, as reported in Column (1) of Table 8. Second, freight volume and student enrollment are used as proxy variables for logistics capacity and human capital, respectively, to examine whether AI application significantly affects the proposed mechanisms. The corresponding results are presented in Columns (2) and (3).

Column (1) of Table 8 shows that the coefficient of AI application is 0.0096 and is statistically significant at the 5% level, indicating that greater AI application significantly improves agricultural product supply chain security.

The freight-volume regression produces a positive coefficient of 0.063, significant at the 10% level. This result suggests that AI application significantly strengthens regional logistics and transportation capacity. Through data analytics, demand forecasting, and intelligent scheduling, AI can improve decision-making in transportation, inventory management, and distribution, thereby enhancing supply chain visibility, flexibility, and resource coordination efficiency (Wang et al., 2016).

More importantly, as shown in Column (2) of Table 8, logistics capacity positively and significantly affects supply chain security (coefficient = 0.0076). Improved logistics capacity facilitates the interregional circulation of agricultural products, shortens transportation time and supply chain response cycles, and enables the reallocation of transport capacity and the selection of alternative routes when logistics nodes are disrupted. These improvements reduce the risks of product spoilage, transportation delays, and supply interruptions. The results therefore support Hypothesis H2a.

For human capital, the estimated coefficient is 0.042 and reaches significance at the 1% level, indicating that AI application promotes regional human capital accumulation. Technological progress not only replaces certain routine and repetitive tasks but also increases demand for nonroutine cognitive skills, problem-solving capabilities, and complex communication skills (Autor et al., 2003).

As AI application deepens, the expected returns to education and skills training increase. Firms and regional governments consequently have stronger incentives to cultivate workers with combined expertise in digital technologies, data analytics, and supply chain management. Furthermore, as reported in Column (3) of Table 8, human capital significantly enhances supply chain security (coefficient = 0.0481, $p < 0.01$). A higher level of human capital improves the capacity to absorb, interpret, and apply AI technologies and strengthens the risk identification, organizational coordination, and emergency-response capabilities of supply chain participants.

This finding is consistent with evidence that innovative human capital facilitates knowledge diffusion and technological absorption, thereby strengthening supply chain resilience (Zhou et al., 2025). AI can therefore improve agricultural product supply chain security by promoting human capital accumulation, supporting Hypothesis H2b. Furthermore, to rigorously verify the mediating mechanisms, we employed the Bootstrap test (1,000 replications for logistics and 200 for human capital). The results confirm that both proposed mechanisms are statistically valid. Specifically, the bias-corrected 95% confidence intervals are [0.00002, 0.00113] for logistics capacity and [0.00047, 0.00361] for human capital, both strictly excluding zero. These findings provide robust empirical support for Hypotheses H2a and H2b.

TABLE 7 Endogeneity test results.

	First-stage	Second-stage (IV-2SLS)
L.ln_ai	0.3414*	
	(0.1988)	
L2.ln_ai	0.1661***	
	(0.0212)	
ln_ai		0.0188**
		(0.0085)
Observations	3,270	3,270
Controls	Yes	Yes
Province FE	Yes	Yes
Country FE	Yes	Yes
Year FE	Yes	Yes
R^2	0.9787	0.0005

Robust standard errors in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. First-stage F-statistic = 39.95; Hansen J p-value = 0.5873; Endogeneity test p-value = 0.3668; Oster Delta = 1.000. The R^2 reported in the second-stage is the within-R^2 after absorbing the high-dimensional fixed effects (province, country, and year), which is why it is numerically lower than the overall R^2 in Table 4. All models control for province, country, and year fixed effects, which are absorbed using the ivreghdfe command.

5.2 Moderation analysis

To further examine how external environmental conditions shape the effect of AI application on agricultural product supply chain security, this study introduces the food consumer price level and institutional quality of importing countries as moderating variables. Interaction terms between each moderating variable and AI application are constructed and included in the regression model. The results are reported in Columns (4) and (5) of Table 7.

The interaction between AI application and the food consumer price indicator has a coefficient of −0.0029 and is significant at the 1%

TABLE 8 Results of the mechanism and moderation analyses.

	Benchmark effect	Freight mechanism	Human mechanism	Cpi moderation	Inst moderation
ln_ai	0.0096**	0.0091**	0.0076**	0.0106**	0.0098**
	(0.0043)	(0.0040)	(0.0031)	(0.0044)	(0.0043)
ln_freight		0.0076			
		(0.0098)			
ln_human			0.0481***		
			(0.0115)		
inter_ai_cpi				−0.0029***	
				(0.0007)	
inter_ai_inst					0.0017**
					(0.0006)
Observations	3,870	3,870	3,870	3,870	3,870
Province FE	Yes	Yes	Yes	Yes	Yes
ASEAN FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
R^2	0.9285	0.9286	0.9303	0.9289	0.9292

Province-clustered robust standard errors are reported in parentheses. (*$p < 0.10$), (**$p < 0.05$), and (***$p < 0.01$). The significance of the indirect effects is formally verified by the Bootstrap test, with bias-corrected 95% confidence intervals strictly excluding zero.

level. This finding indicates that food consumer price levels negatively moderate the effect of AI application on agricultural product supply chain security.

Food prices are jointly determined by supply-and-demand fundamentals, energy markets, financial conditions, and external shocks. Rising and volatile food prices therefore increase uncertainty in both consumer demand and the business environment (Tadesse et al., 2014). When food consumer prices in an importing country are relatively high, consumers may adjust their purchase quantities and consumption structures, while importers may revise orders, inventories, and pricing strategies more frequently. Consequently, historical data become less representative of future demand.

Such changes increase the difficulty of AI-based demand forecasting and resource allocation and raise procurement, storage, and coordination costs for supply chain participants. Higher food consumer prices therefore weaken the positive effect of AI application on agricultural product supply chain security. Hypothesis $_{H3}$ is thus supported.

The interaction with institutional quality is positive at 0.0017 and statistically significant at the 5% level. This result indicates that institutional quality positively moderates the effect of AI application on agricultural product supply chain security.

The institutional conditions of importing countries, as well as institutional differences between exporting and importing countries, influence bilateral trade. The institutional quality of destination markets is particularly important for trade in agricultural products and natural resources (Álvarez et al., 2018). Stronger institutional quality increases policy stability, contract enforceability, and regulatory transparency. It also reduces opportunistic behavior, information asymmetry, and institutional transaction costs in cross-border trade and strengthens the willingness of supply chain participants to share information on orders, logistics, and product quality.

Under such institutional conditions, AI-generated information on forecasting, traceability, and risk early warning can be translated more effectively into coordinated decisions and practical actions. Institutional quality therefore strengthens the contribution of AI application to supply chain stability and recovery capacity. Hypothesis H_4 is thus supported.

Our findings broadly align with recent studies confirming the positive role of AI in supply chain resilience (Zhang and Zhang, 2026; Tang et al., 2025). Specifically, the significant mediating role of logistics capacity echoes El Bhilat et al. (2024), who found that AI improves agri-food supply chain performance by enhancing distribution network efficiency. However, our results differ from some firm-level studies that report uniform benefits of AI. We find that the positive effect is concentrated in eastern China and in provinces with a stronger initial AI foundation. This discrepancy may be attributed to the digital divide and complementary infrastructure. As Forman et al. (2012) argued, the economic returns to digital technologies are highly dependent on regional endowments. Unlike studies focusing solely on domestic supply chains, our cross-border setting reveals that the AI effect is weakened by high food consumer prices in destination markets but strengthened by strong institutional quality. This extends the findings of Álvarez et al. (2018) by showing that institutional quality not only facilitates trade directly but also acts as a crucial boundary condition for the efficacy of digital technologies. Overall, these comparisons highlight the importance of contextual factors in translating AI investments into supply chain security.

6 Conclusions and policy implications

Evidence from the 2011–2023 province–ASEAN country panel indicates that provincial AI application is positively associated with agricultural product supply chain security. The relationship remains stable across the robustness tests and is stronger in eastern China, in provinces with a better initial AI foundation, and in trade relationships involving less agriculture-dependent ASEAN economies. Logistics capacity and human capital account for part of this effect. Food-price pressure weakens the contribution of AI, whereas institutional quality reinforces it.

A further implication is that AI should not be viewed simply as a substitute for conventional machinery or labor. Within a cross-border agricultural supply chain, its more important function is to connect information that was previously separated across firms, regions, and stages of circulation. The value of an intelligent system depends on whether production data can be linked with inventory records, transport capacity, customs information, quality inspection, and changes in destination-market demand. When these connections are incomplete, additional technological equipment may increase data generation without producing better coordination. When information standards, operating procedures, and organizational responsibilities are clearly defined, the same technology can support earlier warning, faster adjustment, and more consistent quality control. The practical emphasis should therefore shift from the amount of intelligent equipment installed to the extent to which AI is embedded in actual supply chain decisions. This perspective is especially relevant to agricultural products, for which delays, temperature changes, inspection problems, and inaccurate demand judgments can rapidly translate into physical losses and supply instability.

Based on the empirical findings, this study proposes the following targeted policy implications.

First, differentiated AI development strategies should be implemented to address regional imbalances. Our formal subgroup tests confirm that the effect is significantly stronger in eastern provinces ($p = 0.022$). Therefore, while eastern China should continue to leverage its digital infrastructure to deepen cross-border AI applications, greater policy support—such as fiscal subsidies, digital infrastructure investment, and talent introduction—should be directed toward central and western provinces to narrow the regional digital divide and enhance their technological absorptive capacity. Second, AI-enabled cross-border cold-chain logistics and traceability systems should be prioritized, given the confirmed mediating role of logistics capacity. The empirical results indicate that AI improves supply chain security by enhancing logistics capacity. Policymakers should therefore promote the coordinated application of AI, IoT, and blockchain in batch identification, temperature monitoring, and quality inspection. Special attention should be paid to mutual recognition of inspection and quarantine standards between China and ASEAN countries to reduce border clearance delays and product spoilage. Third, human capital accumulation should be strengthened to support AI adoption, as evidenced by its significant mediating effect. AI application increases the demand for compound skills in data analytics and supply chain management. China should strengthen cooperation among universities, vocational institutions, and firms across ASEAN countries. Targeted digital skills training should be provided to agricultural producers, logistics enterprises, and SME exporters, particularly in underdeveloped

regions, to convert AI's informational advantages into practical risk-response capabilities. Fourth, a joint food price monitoring and early-warning mechanism should be established. Our moderation analysis reveals that high food consumer prices in importing countries weaken the positive effect of AI. Thus, China and ASEAN countries should enhance data sharing on agricultural prices, inventories, and weather conditions. AI technologies should be deployed to detect abnormal price movements and supply shortages, while contingency plans for reserve adjustments and alternative sourcing should be developed to mitigate the negative impact of price volatility on AI efficacy.Fifth, institutional coordination under the RCEP framework should be deepened. The findings demonstrate that strong institutional quality in importing countries positively moderates the AI effect. Therefore, greater alignment in rules of origin, technical standards, cross-border data flows, and digital trade regulations is urgently needed. China should respect the developmental stages and data governance systems of ASEAN countries and establish a stable, inclusive regional cooperation mechanism through mutual recognition of rules and multilevel consultation, thereby creating a favorable institutional environment for AI to function effectively. Additionally, when promoting cross-border agricultural trade, policymakers should prioritize ASEAN countries with lower agricultural dependence, where our formal subgroup tests confirm a statistically more robust AI effect ($p = 0.007$). For highly agriculture-dependent markets, a more gradual and targeted approach should be adopted.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

HL: Project administration, Conceptualization, Supervision, Funding acquisition, Writing – review & editing. MG: Formal analysis, Writing – original draft, Methodology, Data curation, Software. YD: Writing – review & editing, Investigation, Resources, Validation. WL: Writing – review & editing, Supervision, Conceptualization, Funding acquisition. YL: Writing – review & editing, Investigation, Data curation, Validation.

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Conflict of interest

The author(s) declared that this work was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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References

Acemoglu, D., and Restrepo, P. (2020). Robots and jobs: evidence from US labor markets. *J. Polit. Econ.* 128, 2188–2244. doi: 10.1086/705716

Akhavan Chayjan, K., Razmi, J., and Hassanzadeh Amin, S. (2025). An analytical investigation of inflation's effects on supply chain strategies. *Supply Chain Anal.* 12:100168. doi: 10.1016/j.sca.2025.100168

Alekseeva, L., Azar, J., Giné, M., Samila, S., and Taska, B. (2021). The demand for AI skills in the labor market. *Labour Econ.* 71:102002. doi: 10.1016/j.labeco.2021.102002

Álvarez, I. C., Barbero, J., Rodríguez-Pose, A., and Zofío, J. L. (2018). Does institutional quality matter for trade? Institutional conditions in a sectoral trade framework. *World Dev.* 103, 72–87. doi: 10.1016/j.worlddev.2017.10.010

Anderson, J. E., and Marcouiller, D. (2002). Insecurity and the pattern of trade: an empirical investigation. *Rev. Econ. Stat.* 84, 342–352. doi: 10.1162/003465302317411587

Autor, D. H., Levy, F., and Murnane, R. J. (2003). The skill content of recent technological change: an empirical exploration. *Q. J. Econ.* 118, 1279–1333. doi: 10.1162/003355303322552801

Awokuse, T., Lim, S., Santeramo, F., and Steinbach, S. (2024). Robust policy frameworks for strengthening the resilience and sustainability of agri-food global value chains. *Food Policy* 127:102714. doi: 10.1016/j.foodpol.2024.102714

Banerjee, A., Duflo, E., and Qian, N. (2020). On the road: access to transportation infrastructure and economic growth in China. *J. Dev. Econ.* 145:102442. doi: 10.1016/j.jdeveco.2020.102442

Bartling, B., Fehr, E., Huffman, D., and Netzer, N. (2025). The complementarity between trust and contract enforcement. *Econ. J.* 136:ueaf077. doi: 10.1093/ej/ueaf077

Becker, G. S. (1962). Investment in human capital: a theoretical analysis. *J. Polit. Econ.* 70, 9–49. doi: 10.1086/258724

Bresnahan, T. F., Brynjolfsson, E., and Hitt, L. M. (2002). Information technology, workplace organization, and the demand for skilled labor: firm-level evidence. *Q. J. Econ.* 117, 339–376. doi: 10.1162/003355302753399526

Cameron, A. C., and Miller, D. L. (2015). A practitioner's guide to cluster-robust inference. *J. Hum. Resour.* 50, 317–372. doi: 10.3368/jhr.50.2.317

Ceptureanu, E. G., Ferraro, G., Ceptureanu, S. I., Lazar, R., Florescu, M., Matei, A., et al. (2025). Impact of artificial intelligence and blockchain on supply chain resilience under influence of change management. *Soft Comput.* 29, 3617–3625. doi: 10.1007/s00500-025-10564-5

Coase, R. H. (1937). The nature of the firm. *Economica* 4, 386–405. doi: 10.1111/j.1468-0335.1937.tb00002.x

Cohen, W. M., and Levinthal, D. A. (1990). Absorptive capacity: a new perspective on learning and innovation. *Adm. Sci. Q.* 35, 128–152. doi: 10.2307/2393553

Comin, D., and Hobijn, B. (2010). An exploration of technology diffusion. *Am. Econ. Rev.* 100, 2031–2059. doi: 10.1257/aer.100.5.2031

Comin, D., and Mestieri, M. (2018). If technology has arrived everywhere, why has income diverged? *Am. Econ. J. Macroecon.* 10, 137–178. doi: 10.1257/mac.20150175

Culot, G., Podrecca, M., and Nassimbeni, G. (2024). Artificial intelligence in supply chain management: a systematic literature review of empirical studies and research directions. *Comput. Ind.* 162:104132. doi: 10.1016/j.compind.2024.104132

De Groot, H. L. F., Linders, G. J., Rietveld, P., and Subramanian, U. (2004). The institutional determinants of bilateral trade patterns. *Kyklos* 57, 103–123. doi: 10.1111/j.0023-5962.2004.00245.x

Distefano, T., Laio, F., Ridolfi, L., and Schiavo, S. (2018). Shock transmission in the international food trade network. *PLoS One* 13:e0200639. doi: 10.1371/journal.pone.0200639.

Domingues, I., Queiroz, M. M., and Wamba, S. F. (2026). Institutional voids in supply chains and digital transformation: returning to the roots to reframe the future. *Manag. Rev. Q.* doi: 10.1007/s11301-026-00591-3

Duarte, M., and Restuccia, D. (2010). The role of the structural transformation in aggregate productivity. *Q. J. Econ.* 125, 129–173. doi: 10.1162/qjec.2010.125.1.129

Dubey, R., Bryde, D. J., Dwivedi, Y. K., Graham, G., Foropon, C., Papadopoulos, T., et al. (2023). Dynamic digital capabilities and supply chain resilience: the role of government effectiveness. *Int. J. Prod. Econ.* 258:108790. doi: 10.1016/j.ijpe.2023.108790

El Bhilat, E. M., El Jaouhari, A., and Hamidi, L. S. (2024). Assessing the influence of artificial intelligence on agri-food supply chain performance: the mediating effect of distribution network efficiency. *Technol. Forecast. Soc. Chang.* 200:123149. doi: 10.1016/j.techfore.2023.123149

Forman, C., Goldfarb, A., and Greenstein, S. (2012). The internet and local wages: a puzzle. *Am. Econ. Rev.* 102, 556–575. doi: 10.1257/aer.102.1.556

Francois, J., and Manchin, M. (2013). Institutions, infrastructure, and trade. *World Dev.* 46, 165–175. doi: 10.1016/j.worlddev.2013.02.009

Fujii, H., and Managi, S. (2018). Trends and priority shifts in artificial intelligence technology invention: a global patent analysis. *Econ. Anal. Policy* 58, 60–69. doi: 10.1016/j.eap.2017.12.006

Galbraith, J. R. (1974). Organization design: an information processing view. *Interfaces* 4, 28–36. doi: 10.1287/inte.4.3.28

Gonzales, J. T. (2023). Implications of AI innovation on economic growth: a panel data study. *J. Econ. Struct.* 12:13. doi: 10.1186/s40008-023-00307-w

Green, R., Cornelsen, L., Dangour, A. D., Turner, R., Shankar, B., Mazzocchi, M., et al. (2013). The effect of rising food prices on food consumption: systematic review with meta-regression. *BMJ* 346:f3703. doi: 10.1136/bmj.f3703

Guimarães, P., and Portugal, P. (2010). A simple feasible procedure to fit models with high-dimensional fixed effects. *Stata J.* 10, 628–649. doi: 10.1177/1536867X1101000406

Hellegers, P. (2022). Food security vulnerability due to trade dependencies on Russia and Ukraine. *Food Secur.* 14, 1503–1510. doi: 10.1007/s12571-022-01306-8.

Huang, I. Y., Forero, O. A., Wagner-Medina, E. V., et al. (2025). Resilience of food supply systems to sudden shocks: a global review and narrative synthesis. *Glob. Food Secur.* 44:100842. doi: 10.1016/j.gfs.2025.100842

Jafari, Y., Engemann, H., and Zimmermann, A. (2024). The multiple dimensions of resilience in agricultural trade networks. *Q. Open* 4:qoae024. doi: 10.1093/qopen/qoae024

Jauhar, S. K., Harinath, S., Krishnaswamy, V., and Paul, S. K. (2025). Explainable artificial intelligence to improve the resilience of perishable product supply chains by leveraging customer characteristics. *Ann. Oper. Res.* 354, 103–142. doi: 10.1007/s10479-024-06348-z

Kang, Q., and Lin, G. H. (2021). The impact mechanism of industrial robots on employment: Industrial structure upgrading or rationalization? *Soft Sci.* 35, 20–27. doi: 10.13956/j.ss.1001-8409.2021.04.04

Kassa, A., Kitaw, D., Stache, U., Beshah, B., and Degefu, G. (2023). Artificial intelligence techniques for enhancing supply chain resilience: a systematic literature review, holistic framework, and future research. *Comput. Ind. Eng.* 186:109714. doi: 10.1016/j.cie.2023.109714

Kromann, L., Malchow-Møller, N., Skaksen, J. R., and Sorensen, A. (2020). Automation and productivity—a cross-country, cross-industry comparison. *Ind. Corp. Chang.* 29, 265–287. doi: 10.1093/icc/dtz039

Lang, K., and Zhao, K. (2024). Supply chain security: definition, measurement, and international comparison. *Q. J. Int. Polit.* 9, 108–134. doi: 10.16513/j.cnki.qjip.2024.0019

Lee, H. L., Padmanabhan, V., and Whang, S. (1997). Information distortion in a supply chain: the bullwhip effect. *Manag. Sci.* 43, 546–558. doi: 10.1287/mnsc.43.4.546

Lin, L., and Zhang, X. (2025). Research on the impact of enterprise artificial intelligence on supply chain resilience: empirical evidence from Chinese listed companies. *Sustainability* 17:8576. doi: 10.3390/su17198576

Liu, Z., Yu, X., Liu, N., et al. (2025). Integrating AI with detection methods, IoT, and blockchain to achieve food authenticity and traceability from farm-to-table. *Trends Food Sci. Technol.* 158:104925. doi: 10.1016/j.tifs.2025.104925

Lu, W. X., and Meng, X. (2021). Industrial robot application, employment market structure adjustment and service trade development. *Int. Econ trade res.* 37, 4–20. doi: 10.13687/j.cnki.gjjmts.20210816.001

Luo, S., Lei, W., and Hou, P. (2024). Impact of artificial intelligence technology innovation on total factor productivity: an empirical study based on provincial panel data in China. *Natl. Acc. Rev.* 6, 172–194. doi: 10.3934/NAR.2024008

Luo, W., Tang, L., Yang, Y., and Zou, X. (2025). Robots as guardians: industrial automation and workplace safety in China. *J. Dev. Econ.* 172:103381. doi: 10.1016/j.jdeveco.2024.103381

Ma, L., Luo, X., and Xi, M. (2025). The impact of regional artificial intelligence development on the resilience of enterprise supply chains. *Int. Rev. Econ. Financ.* 102:104305. doi: 10.1016/j.iref.2025.104305

Nikookar, E., and Yanadori, Y. (2022). Preparing supply chain for the next disruption beyond COVID-19: managerial antecedents of supply chain resilience. *Int. J. Oper. Prod. Manag.* 42, 59–90. doi: 10.1108/IJOPM-04-2021-0272

Ou, J., Zheng, Z., Ou, X., and Zhang, N. (2024). Smart city construction, artificial intelligence development, and the quality of export products: a study based on micro-level data of Chinese enterprises. *Sustainability* 16:8640. doi: 10.3390/su16198640

Oster, R. (2019). Unobservable selection and coefficient stability: Theory and evidence[J]. *J. Bus. Econ. Stat.* 37, 187–204. doi: 10.1080/07350015.2016.1227711

Poo, M. C. P., Wang, T., and Yang, Z. (2024). Global food supply chain resilience assessment: a case in the United Kingdom. *Transp. Res. A Policy Pract.* 181:104018. doi: 10.1016/j.tra.2024.104018

Reitano, M., Segovia, M. S., and Nayga, R. M. Jr. (2025). A systematic review on the impact of artificial intelligence in the agri-food supply chain. *Food Policy* 137:102983. doi: 10.1016/j.foodpol.2025.102983

Ritzel, C., Möhring, A., and von Ow, A. (2024). Vulnerability assessment of food imports—conceptual framework and empirical application to the case of Switzerland. *Heliyon* 10:e27058. doi: 10.1016/j.heliyon.2024.e27058.

Rojas-Reyes, J. J., Rivera-Cadavid, L., and Peña-Orozco, D. L. (2024). Disruptions in the food supply chain: a literature review. *Heliyon* 10:e34730. doi: 10.1016/j.heliyon.2024.e34730.

Sadeghi, R. K., Ojha, D., Kaur, P., Mahto, R. V., and Dhir, A. (2024). Explainable artificial intelligence and agile decision-making in supply chain cyber resilience. *Decis. Support Syst.* 180:114194. doi: 10.1016/j.dss.2024.114194

Scarton, G., Benini, N., and Formentini, M. (2026). AI-enhanced demand forecasting: an organizational information processing view. *Int. J. Phys. Distrib. Logist. Manag.* 56, 485–508. doi: 10.1108/IJPDLM-01-2025-0022

Shen, Y., and Zhang, X. (2024). The impact of artificial intelligence on employment: the role of virtual agglomeration. *Humanit. Soc. Sci. Commun.* 11:122. doi: 10.1057/s41599-024-02647-9

Song, Y., Song, Y., and Wang, Q. (2026). Smart agriculture development: how can rural digital transformation enhance the resilience of food security? *Foods* 15:426. doi: 10.3390/foods15030426.

Sunmola, F., and Baryannis, G. (2024). Artificial intelligence opportunities for resilient supply chains. *IFAC-PapersOnLine* 58, 813–818. doi: 10.1016/j.ifacol.2024.09.195

Tadesse, G., Algieri, B., Kalkuhl, M., and von Braun, J. (2014). Drivers and triggers of international food price spikes and volatility. *Food Policy* 47, 117–128. doi: 10.1016/j.foodpol.2013.08.014

Tang, H., Wu, K., and Zhou, J. (2025). Smarter supply chains, stronger resilience? The impact of AI on preparation, response, and recovery. *Econ. Lett.* 254:112488. doi: 10.1016/j.econlet.2025.112488

Teece, D. J. (2007). Explicating dynamic capabilities: the nature and microfoundations of (sustainable) enterprise performance. *Strateg. Manag. J.* 28, 1319–1350. doi: 10.1002/smj.640

Tendall, D. M., Joerin, J., Kopainsky, B., Edwards, P., Shreck, A., Le, Q. B., et al. (2015). Food system resilience: defining the concept. *Glob. Food Secur.* 6, 17–23. doi: 10.1016/j.gfs.2015.08.001

Toorajipour, R., Sohrabpour, V., Nazarpour, A., Oghazi, P., and Fischl, M. (2021). Artificial intelligence in supply chain management: a systematic literature review. *J. Bus. Res.* 122, 502–517. doi: 10.1016/j.jbusres.2020.09.009

Wang, S., Chen, X., and Han, N. (2026). Intelligent development of manufacturing enterprises and supply chain resilience: a perspective based on internal capabilities and external linkages. *Expert Syst. Appl.* 310:131338. doi: 10.1016/j.eswa.2026.131338

Wang, G., Gunasekaran, A., Ngai, E. W. T., and Papadopoulos, T. (2016). Big data analytics in logistics and supply chain management: certain investigations for research and applications. *Int. J. Prod. Econ.* 176, 98–110. doi: 10.1016/j.ijpe.2016.03.014

Williamson, O. E. (1979). Transaction-cost economics: the governance of contractual relations. *J. Law Econ.* 22, 233–261. doi: 10.1086/466942

Williamson, O. E. (2000). The new institutional economics: taking stock, looking ahead. *J. Econ. Lit.* 38, 595–613. doi: 10.1257/jel.38.3.595

Wu, L., Zhang, Z., Huang, J., Su, I.-H., and Tian, S. (2025). Digital technologies and supply chain resilience: a resource-action-performance perspective. *Inf. Syst. Front.* 27, 2137–2158. doi: 10.1007/s10796-025-10595-1

Xiao, J., and Boschma, R. (2023). The emergence of artificial intelligence in European regions: the role of a local ICT base. *Ann. Reg. Sci.* 71, 747–773. doi: 10.1007/s00168-022-01181-3

Yang, L., Huang, M., and Wang, H. (2025). Artificial intelligence and resilience of supply chain in China's listed firms: insights into vertical spillover effects. *Financ. Res. Lett.* 85:107984. doi: 10.1016/j.frl.2025.107984

Yu, Z., Liu, H., and Xing, C. (2026). Digital intelligence technology adoption and supply chain security of manufacturing firms: empirical evidence from China. *Sci. Rep.* 16:10356. doi: 10.1038/s41598-026-41349-x.

Zhang, J., and Zhang, Q. (2026). Artificial intelligence and supply chain stabilization. *Financ. Res. Lett.* 89:109322. doi: 10.1016/j.frl.2025.109322

Zhao, K., and Lang, K. (2022). Supply chain security amid China–US competition. *Northeast. Asia Forum* 31, 19–39. doi: 10.13654/j.cnki.naf.2022.02.002

Zhou, L., Tang, C., and Cao, Y. (2025). Innovative human capital, government support for science and technology policy, and supply chain resilience. *Financ. Res. Lett.* 74:106741. doi: 10.1016/j.frl.2025.106741