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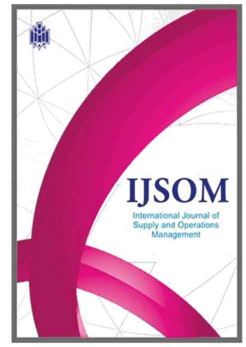

Artificial Intelligence Capabilities and Their Influence on Supply Chain Resilience and Performance: Insights from Agri-Food Firms in an Emerging Economy

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Abstract

Artificial Intelligence (AI) is emerging as a crucial tool to enhance supply chain performance and resilience in global agricultural supply chains, which are being disrupted by market volatility and climate change. This study examines how AI capabilities are used in agribusinesses in Vietnam's Mekong Delta, a growing industry. The study intends to examine how supply chain collaboration (SC), environmental uncertainty (EU), and AI technological compatibility (AT) affect Willingness to Adopt AI (WA), as well as how these factors affect Supply Chain Resilience (SR) and Supply Chain Performance (SP). Utilizing the Resource-Based View (RBV) and the Technology–Organization–Environment (TOE) framework, the study sent a questionnaire to 223 businesses, obtaining a 94% valid response rate. This study employs SmartPLS software to perform analysis based on the Partial Least Squares Structural Equation Modeling (PLS-SEM) approach. The findings indicate that AT, SC, and EU are significant determinants of the readiness for WA, with T-Values of 4.822, 6.697, and 4.378, respectively. At the same time, WA has the strongest impact on SR (T-Value = 8.031) and also influences SP (T-Value = 4.482). The results emphasize the potential of AI to reduce disruptions and enhance operational efficiency, particularly in emerging markets. The study is constrained by its geographical focus on the Mekong Delta and the reliance on cross-sectional survey data, which limit generalizability and dynamic analysis. Future studies should broaden their focus and investigate certain AI technologies to enhance comprehension of AI applications inside agricultural supply chains.

Keywords: Artificial Intelligence (AI); Supply Chain Resilience (SR); Supply Chain Performance (SP); Agri-Food Systems; Emerging Markets.

1. Introduction

Modern global supply chains have evolved into complex networks of organizations that traverse geographical and political boundaries (Sharma et al., 2024). These supply chains face growing pressures from frequent disruptions, particularly in the agri-food sector, which is susceptible to climate variation, market changes, and logistical challenges (Ritambara et al., 2024). Over the last twenty years, the agri-food sector has become one of the most significantly impacted industries due to its sensitivity to climate fluctuations, product perishability, seasonality, and reliance on labor-intensive processes (Ahmad et al., 2024). Such characteristics render it vulnerable to shocks like global

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pandemics, geopolitical conflicts, trade embargoes, and natural disasters (FSIN, 2024). Amid these disruptions, AI has emerged as a transformative force, providing solutions for predictive analytics, demand forecasting, and real-time decision-making (Feng et al., 2023; Pandey & Mishra, 2024). Recent studies show that AI enhances supply chain efficiency through predictive analytics and real-time decision-making, with the potential to reduce costs by up to 15% (Chui et al., 2023).

AI technologies, such as machine learning, natural language processing, computer vision, and robotics, enable companies to manage vast quantities of data and make informed decisions promptly (Tseng & Kiang, 2025; Ahmad et al., 2024). In emerging economies, agri-food supply chains encounter heightened challenges due to limited infrastructure, varying regulatory environments, and market instability (Pandey & Mishra, 2024). AI capabilities offer a potential pathway to enhanced SR and SP, although adoption remains inconsistent and depends on various contextual factors (Liu et al., 2024; Wang & Pan, 2022; Lee et al., 2022). Specifically, generative AI advances agri-food systems through predictive analytics, food design, and sustainability initiatives. Applications include disease modeling, supply chain optimization, and climate change mitigation (Bran et al., 2024; Pandey & Mishra, 2024). New technologies like transformers and large language models are fostering innovation in agriculture and food production (Nayal et al., 2021; Sharifmousavi et al., 2024). Although the benefits of adopting AI technology are numerous, there are risks associated with its integration. After implementation, companies must invest in more advanced infrastructure or access to valuable datasets to retain a long-term competitive edge, shifting the focus of competition toward technological assets and data resources. Furthermore, the integration of AI systems in developing regions is constrained by substantial upfront expenses, insufficient digital readiness, and issues related to information security and potential algorithmic discrimination, which need to be tackled to ensure inclusive advantages. While AI is unlikely to fully substitute human labor, an increasing number of work processes will be automated, putting employees who fail to adapt to these technological changes at risk of job displacement (Ritambara et al., 2024; Kalimuthu et al., 2024).

Despite the increasing interest in AI and supply chain management (SCM), research on the agri-food sector in emerging economies remains notably scarce. Most existing studies focus on AI in highly technological or industrial supply chains, like electronics and automotive (Cicerelli & Ravetti., 2024; Singh et al., 2025; Cruz & Ignacio, 2023), often taking a technological perspective rather than considering contextual factors. Few studies comprehensively investigate how AI adoption is influenced by supply chain-specific conditions such as uncertainty, collaboration, and resource limitations, elements that tend to be intensified in emerging markets. Additionally, there has been limited investigation into how organizational conditions and external environmental elements collectively influence readiness for AI adoption, or how such adoption impacts broader outcomes like resilience and performance. The role of willingness to adopt AI, a crucial behavioral and organizational readiness dimension, has not been sufficiently incorporated into AI and supply chain research. To fill this gap, this paper proposes a conceptual framework that connects technological compatibility, environmental uncertainty, and collaboration to AI adoption willingness, as well as its impact on SR and SP. This study seeks to examine how AI capabilities influence SR and SP, particularly within agri-food firms operating in emerging economies. To support these goals, the study objectives include examining the linkage between AI technological compatibility and readiness to adopt AI, assessing how environmental uncertainty and supply chain collaboration influence this willingness, and evaluating the effects of AI adoption readiness on SR and SP.

It integrates the TOE framework with RBV and behavioral constructs to create a comprehensive model of AI adoption and its implications for SR and SP. This research enhances the understanding of AI's role within agri-food supply chains, a field that is often overlooked in digital transformation literature, especially regarding emerging economies. By concentrating on environmental uncertainty and collaboration, the study highlights the intricate external and relational factors that shape digital adoption. The results provide actionable insights for agri-food companies looking to improve resilience and efficiency through AI implementation, benefiting policymakers, development agencies, and supply chain professionals alike. The Mekong Delta (Vietnam), a key player in the regional and global agri-food export market, faces challenges such as a fragmented logistics network and the impacts of climate change, making it an ideal case for studying SR enabled by AI. Conceptually, the study looks at supply chain stakeholders at the firm level (e.g., producers, processors, distributors) and explores their interactions with AI technologies in areas such as procurement, logistics, and customer service. First, we advance a unified model that integrates TOE, RBV, and behavioral constructs to explain AI adoption and its implications for SR and SP in agrifood supply chains. Second, we foreground an emerging economy context, the Mekong Delta (Vietnam), to illuminate how environmental uncertainty and supply chain collaboration shape digital adoption pathways. Third, we adopt a lens at the firm level that maps concrete AI touchpoints across procurement, logistics, and customer service, offering an actionable pathway for implementation.

This study engages explicitly with the Sustainable Development Goals. In particular, the model speaks to SDG 9 (industry, innovation and infrastructure) through AI capability and adoption, SDG 12 (responsible consumption and production) through sustainability performance, SDG 13 (climate action) through supply chain resilience to climate related shocks, SDG 8 (decent work and economic growth) through efficiency and productivity gains, and SDG 17 (partnerships for the goals) through inter firm collaboration. Throughout the paper, we interpret the findings with reference to these goals.

The organization of this research is structured as follows: it starts with an overview of prior scholarly work and a description of the proposed theoretical framework and research propositions, then proceeds to outline the dataset and analytical techniques employed. Subsequently, the study presents its empirical results, ending with an examination of the study's contributions and suggestions for future investigation.

2. Literature Review and Research Hypothesis

2.1. Literature Review

The Technology-Organization-Environment (TOE) and the Resource-Based View (RBV) framework

The TOE framework is an organizational-level model designed to analyze elements impacting the acceptance of technological advancements (Tornatzky et al., 1990). TOE stands out by integrating internal and external factors, encompassing three dimensions: Technology, Organization, and Environment. The Technology dimension evaluates characteristics such as relative advantage, compatibility, complexity, security, and observability, which affect the technology's fit with the organization (Al Hadwer et al., 2021; Chittipaka et al., 2023; Nguyen et al., 2022). The Organization dimension focuses on internal resources, including top management support, firm size, IT resources, financial capabilities, and entrepreneurial/technological orientation, which determine the capacity for technology implementation (Chittipaka et al., 2023; Peggy et al., 2022). The Environment dimension examines external factors such as competitive pressure, government support, business partner pressure, perceived trends, and regulatory frameworks, which either promote or hinder adoption (Nguyen et al., 2022; Peggy et al., 2022). TOE is flexibly applied in contexts like cloud computing, blockchain, online retailing, and remote work, either independently or in combination with theories such as DOI (Diffusion of Innovation) or TPB (Theory of Planned Behavior). With strong empirical support, TOE is an effective tool for studying innovation adoption behavior in organizations.

The RBV is a strategic theory that views a firm as a collection of unique resources, explaining performance differences due to heterogeneity and path dependence (Lockett et al., 2009; Lockett & Thompson, 2001). RBV asserts that a sustainable competitive advantage arises from resources possessing attributes of value, rarity, inimitability, and non-substitutability, including intangible assets (such as reputation systems and knowledge) and organizational capabilities (Barney & Thompson, 1991; Lockett et al., 2009; Clulow et al., 2007; Bromiley & Rau, 2016). The SCA generates profits through resource market imperfections, while management plays a role in identifying sources, combining resources, and developing resources to optimize their value (Lockett et al., 2009). RBV complements theories like transaction cost economics, aiding analysis of supply chain diversification, innovation, and market entry strategies (Lockett & Thompson, 2001). However, RBV faces challenges in measuring resources, circularity issues, and providing actionable recommendations due to resource inimitability (Bromiley & Rau, 2016). Research has also extended to the customer perspective on resource value (Clulow et al., 2007). With its flexibility and, RBV is a powerful tool for understanding supply chains and building competitive advantage.

The model presented in Figure 1 below is the result of this study's combination of the RBV and TOE theories. According to the TOE hypothesis, in particular, H1, H2, and H3 show that supply chain collaboration, environmental uncertainty, and adaptability with AI technology all positively affect businesses' adoption of AI technology.

Artificial Intelligence Capabilities in the Agricultural Supply Chain Context

A critical examination of AI definitions highlights its fundamental capabilities: learning, perception, prediction, interaction, adaptation, and reasoning (Jackson et al., 2024). Specifically, AI systems learn from data to predict, analyze, and make decisions while also interpreting the world through the lens of human-like senses (Hendriksen, 2023). Furthermore, AI can adapt and improve progressively with new data and fluctuating contexts. Its ability to reason, plan, and make decisions is essential for managing complex tasks (Cannas et al., 2023; Wang & Pan, 2022). In supply chains, AI technologies such as machine learning, natural language processing, and robotics support automation, optimization, and data-driven decision-making (Mahraz et al., 2022; Hendriksen, 2023). Among its key applications, demand forecasting stands out as a critical function where AI plays a transformative role. Leveraging large datasets, AI algorithms can detect complex patterns, improve forecast accuracy over time, and thus enable more responsive and cost-effective operations (Vishwakarma et al., 2024; Patalas-Maliszewska et al., 2024; Richey et al., 2023).

In addition, AI is increasingly utilized in manufacturing processes, serving as a crucial technology for boosting the industry's overall competitiveness (Jackson et al., 2024). Initially, general AI technology was recognized for its effectiveness in diagnosing and predicting issues in complex industrial environments (Cannas et al., 2023). A key focus within this domain is enhancing production system throughput, which is vital for production line management and control. This is typically achieved by pinpointing bottleneck machines and optimizing their operations. Machine learning methods leverage sensor data to propose a system diagnostic approach that effectively identifies real-time production limitations and bottlenecks (Gupta et al., 2024; Wang & Pan, 2022). Furthermore, system-level algorithms help determine production quantities and schedules, identify resource utilization timelines, and streamline job releases, routing, and sequencing (Mahraz et al., 2022; Richey et al., 2023). AI and machine learning capabilities allow for real-time updates of stock levels, eliminating the need for tedious inventory counting. AI also enhances warehouse management and resource utilization assessments. It fosters greater transparency, visibility and collaboration among supply chain partners by distributing information promptly to all relevant stakeholders (Mahraz et al., 2022). In summary, AI is applied across various aspects of supply chain processes, including but not limited to transportation, shipping, production, and warehousing activities.

The agricultural value chain involves numerous stages, including planning land use, cultivating crops, preventing and treating diseases, and processing, storing, transporting, and distributing products (Vernier et al., 2021; Aghababaei et al., 2025). Each stage is complex and demands significant skills and knowledge from experts. Furthermore, the diversity and interdependence of these stages create additional challenges in optimizing agricultural processes (Bačiulienė et al., 2023; Wang & Pan, 2022). AI systems tackle this challenge by developing the most effective agricultural strategies, thereby simplifying operations, reducing risks, and improving efficiency across both global and localized segments of the value chain (Feng et al., 2023; El Bhilat et al., 2024). First, AI tools are essential for land use planning, offering advanced analysis of crucial factors like soil quality, weather conditions, and topography. By leveraging advanced artificial intelligence techniques, including predictive analytics, real-time data processing, and interconnected smart devices, modern agricultural systems are now capable of interpreting extensive information gathered from multiple channels such as satellite imagery, field-based soil assessments, and long-term climate records (Liu et al., 2024; Biazar et al., 2025). For instance, computational models like classification algorithms and rule-based systems are employed to assess soil quality by analyzing critical indicators such as acidity, organic composition, and key macronutrients, namely nitrogen, phosphorus, and potassium (Liu et al., 2016). Moreover, AI-driven platforms make use of vegetation indices like NDVI (Normalized Difference Vegetation Index), extracted from remote sensing technologies, to assist farmers in modeling extreme climate events, such as droughts, floods, water scarcity, and heatwaves, thereby strengthening adaptive capacity and minimizing agricultural risks (Jung et al., 2021; Wang & Pan, 2022). By incorporating topographical information, these tools facilitate the selection of ideal terrain for various crops, taking into account factors such as slope, drainage, and microclimate variations (Pandey & Mishra, 2024). As a result, incorporating detailed imagery from advanced Earth observation systems into AI frameworks empowers agricultural producers to formulate well-grounded strategies regarding the efficient distribution of land resources.

Additionally, AI offers significant potential in helping farmers determine optimal times for sowing, spraying herbicides, and assessing the risk of pest infestations (Feng et al., 2023). By leveraging AI and machine learning for real-time crop monitoring, companies can more accurately estimate yields, identify ideal sowing times, and predict the best harvesting periods to enhance profitability (Kalimuthu et al., 2024; Vernier et al., 2021). Furthermore, AI aids in identifying plant diseases, enabling farmers to implement effective management strategies (Rugji et al., 2024; Muhammed et al., 2024). The integration of sensors, machine vision, AI models, and robotics allows for more efficient and precise harvesting processes, reducing crop loss compared to traditional methods (Misra et al., 2022). While AI presents tremendous opportunities for the agricultural sector, researchers still encounter numerous challenges, such as gathering necessary data to build comprehensive databases. Additionally, obstacles to adoption remain, including steep implementation costs, concerns about data quality, and inadequate digital infrastructure (Aghababaei et al., 2025).

Supply Chain Resilience (SR)

Singh et al. (2024) define SR as the ability of a firm to prepare for, adapt to, and swiftly respond to disruptions within its supply chain. Other researchers have noted that resilience encompasses a supply chain's capability to prepare for interruptions, react to unforeseen events, withstand disturbances, restore operations, and recover costs efficiently while sustaining desirable growth levels (Kumawat, 2024; Sharma et al., 2024). After reviewing existing literature on SR, Lee et al. (2022) offer three converging and comprehensive definitions. First, resilience is identified as absorptive capacity related to emergency or disaster preparedness. Second, it denotes adaptive capacity, reflecting the response to emergencies or disasters. Lastly, it is characterized as restorative capacity, which determines recovery from crises or disasters and the competitive advantage achieved thereafter. These three capacities illustrate temporal aspects before, during, and after an emergency or disaster, forming a valuable framework for assessing SR (Zamani et al., 2022; Patalas-Maliszewska et al., 2024). Companies with resilient supply chains can adeptly navigate unexpected disruptions and lessen their adverse effects, ensuring ongoing operations, rapid recoveries, and the capacity to fulfill customer requirements even under challenging conditions (Sharma et al., 2024).

Numerous studies indicate that SR is achievable through flexibility, visibility, and collaboration. Flexibility allows firms to adapt to environmental changes without damage, restructuring their resources as necessary. Visibility ensures that updates are communicated in real time. Collaboration involves the exchange of essential information among companies, which enhances cooperation in the supply chain and facilitates quicker responses to changes (Singh et al., 2023). Additionally, building SR is a gradual process, stemming from the lessons organizations learn from crisis experiences (Khan et al., 2025). These competencies that constitute a resilient supply chain substantially enhance an organization's overall performance and effectively alleviate the adverse impacts of disturbances and operational weaknesses by providing competitive advantages (Nwamekwe & Igbokwe, 2024). It can be asserted that supply chains function more resiliently when all involved companies unite to tackle crises, rather than relying on a single entity's efforts (Riad et al., 2024). Recent crisis oriented studies propose robust and scenario based optimization for agri food supply chains during pandemic and wartime conditions, underscoring the value of preparedness under deep uncertainty (Rahbari et al., 2024, 2025a, 2025b). Our study complements this stream by focusing on firm level adoption mechanisms of data and AI capabilities and on collaboration, which are organizational levers that can be mobilized alongside such planning approaches.

Supply Chain Performance (SP)

SP efficiency plays a vital role in determining organizational effectiveness, particularly within the manufacturing sector, where enhancing process performance and reducing expenditures are key priorities (Lee et al., 2022). It refers to how well a supply chain can manage its processes efficiently and effectively, ensuring optimal use of resources, cost savings, and customer satisfaction. Various metrics such as cost efficiency, speed, reliability, flexibility, and sustainability help organizations evaluate and enhance their supply chain operations (Wang & Pan, 2022). Other researchers propose evaluating SP regarding manufacturing and inventory costs, responsiveness to delivery changes, and partner integration (Huang et al., 2023). Therefore, SP is defined by flexibility, integration, and customer responsiveness (Lee et al., 2022). Flexibility reflects how well supply chain partners can swiftly adapt to market changes. Integration assesses how effectively activities and communication are synchronized, as well as how strategic choices are managed across the supply network. Customer responsiveness indicates how quickly partners fulfill customer needs and desires (Lee et al., 2022).

Measuring SP is vital for businesses to stay competitive, as it allows them to spot inefficiencies and implement strategic enhancements (Biazar et al., 2025). Nonetheless, traditional supply chains frequently struggle to meet customer demands because of inefficiencies, prompting firms to embrace advanced technologies like blockchain and AI for performance improvement Lee et al., 2022; (Liu et al., 2024). Furthermore, performance measurement frameworks assist organizations in assessing their supply chain operations and pinpointing improvement opportunities. Companies that skillfully manage their SP secure a competitive edge by optimizing resources and minimizing operational risks (Liu et al., 2024). As global supply chains grow increasingly complex, businesses must continuously refine their strategies to maintain efficiency and adaptability in ever-changing market conditions (Patalas-Maliszewska et al., 2024; Riad et al., 2024).

To clarify how this study advances prior work, Table 1 contrasts key studies with the present article, with innovations fully highlighted.

Table 1. Comparison of key prior studies and this article (innovations highlighted)

Study (year)	Context/domain	Theory/lens	Method/data	Scope/key constructs	Outcomes considered	Main limitation	How the present article advances (innovations)
Tornatzky & Fleischer (1990)	Foundational innovation adoption across industries	TOE	Conceptual framework	Technology readiness, organizational context, environmental context	Adoption antecedents; no direct supply chain outcomes	No agri food focus; no AI; no resilience or sustainability outcomes	Integrates TOE with RBV and behavioral constructs for AI in agri food supply chains
Barney (1991)	Strategic management	RBV	Conceptual theory	VRIN resources, capabilities, competitive advantage	Firm performance in general terms	Not specific to digital adoption or supply chain resilience	Operationalizes AI capabilities and links them to resilience and sustainability performance
Tseng & Kiang, (2025)	Manufacturing and supply chains	Digital technologies and resilience	Empirical synthesis / surveys (varies by paper)	Industry 4.0 or AI applications for resilience	Supply chain resilience improvements	Limited focus on agri food in emerging economies	Examines agri food firms in the Mekong Delta and tests mediation through willingness to adopt AI and resilience
Lee et al. (2022)	Agriculture and food systems	AI applications in food and agriculture	Review and empirical cases	AI for disease modeling, logistics, forecasting	Operational efficiency; mixed evidence on sustainability	Descriptive focus; lacks integrated adoption framework	Provides a unified adoption to outcome model (TOE + RBV + behavioral) with PLS SEM testing
Liu et al. (2024)	Food supply chains	AI and data analytics	Recent empirical studies	Analytics capabilities; collaboration	Efficiency and service outcomes	Does not model resilience and sustainability jointly; limited emerging economy evidence	Jointly models resilience and sustainability performance and foregrounds collaboration and environmental uncertainty in an emerging economy
This article (current study)	Agri food firms in the Mekong Delta (Vietnam)	Unified model: TOE + RBV + behavioral constructs	PLS SEM; 223 valid firm responses; expert review and pilot test	Technological compatibility, collaboration, environmental uncertainty; willingness to adopt AI; AI capabilities	Supply chain resilience and sustainability performance	Regional sampling; cross sectional design	End to end test of adoption to outcome pathway in an emerging economy, with mediated mechanisms through willingness and resilience

2.2. Research Hypothesis

Artificial Intelligence Technology (AT) and Willingness to Adopt (WA)

User acceptance is crucial for the successful adoption of technology (Wang & Pan, 2022). To leverage the benefits of AI, users must not only accept this technology but also utilize it effectively. Compatibility with existing systems is essential for users to adopt new technologies willingly (Tseng & Kiang, 2025). For instance, when green innovations demand resources unavailable to an organization or necessitate changes that conflict with its strategic goals, implementation can become challenging. Prior studies indicate that compatibility has a positive impact on the adoption of innovations (Vernier et al., 2021; Rugji et al., 2024). A similar perspective applies to adopting AI and its compatibility. Businesses are likely to be more open to implementing AI if they perceive that this technology aligns with their operational needs and innovation criteria (Riad et al., 2024). The TOE framework posits that technological factors pertain to the attributes of emerging innovations, encompassing the underlying technological readiness of firms, including their infrastructure, expertise, competitive strengths, and the degree to which implemented technologies are compatible with incumbent systems (Nayal et al., 2021; Lee et al., 2022). Despite the substantial potential of AI technologies, if they do not integrate smoothly with a business's current operating systems or pose significant challenges during implementation, businesses might postpone or even reject their adoption (Jung et al., 2021). Therefore, the assumptions outlined below are proposed:

Hypothesis 1: A positive association exists between AT and WA.

Supply Chain Collaboration (SC) and Willingness to Adopt

SC refers to a partnership in which businesses exchange information, resources, and risks to enhance their cooperative value, yielding greater benefits than acting independently (Aghababaei et al., 2025; Nayal et al., 2021; Khan et al., 2025). Research indicates that this collaboration entails forming alliances to leverage knowledge and assets, thereby increasing the overall value of cooperation beyond individual efforts (Tseng & Kiang, 2025). Effective coordination between upstream and downstream supply chain partners is crucial for smooth operations, particularly during abrupt shifts in supply-demand dynamics, necessitating the integration of information and resources (Huang et al., 2023). In practical terms, this means that companies must collaborate to ensure the supply chain operates efficiently during these shifts, necessitating the synchronization of business activities and the sharing of resources and information (Wang & Pan, 2022). AI plays a pivotal role in this process by alleviating the cognitive burden from managing vast amounts of data, transforming raw data into actionable insights, and aiding companies in managing supply chain risks (Patalas-Maliszewska et al., 2024; Sharma et al., 2024). Consequently, firms aiming to enhance their collaboration may find their inclination to implement AI technologies increasing. Building on this understanding, this study presents the following hypothesis:

Hypothesis 2: A positive association exists between SC and WA.

Environmental Uncertainty (EU) and Willingness to Adopt

EU is the perceived complexity and unpredictability faced when identifying and integrating technology, along with the instability driven by rapid changes, such as the sudden introduction of new software or components (Tseng & Kiang, 2025; Jackson et al., 2024). The TOE theory posits that environmental factors serve as external pressures and supports influencing an enterprise's technology adoption. These factors pertain to the external environment impacting an organization's readiness to embrace new technologies, which might enhance their willingness to adopt them (Tseng & Kiang, 2025; Liu et al., 2024). In their analysis of the technology innovation literature, researchers highlighted key predictors of innovation adoption, noting that uncertainty significantly affects a firm's decisions to assess and implement new technological innovations (Ritambara et al., 2024; Richey et al., 2023). In a context characterized by increasing unpredictability, organizations often perceive that rapidly embracing emerging technologies provides a strategic advantage, which is essential for enhancing supply chain alignment and improving operational performance (Sharma et al., 2024; Vadlamudi, 2019). Consequently, it is expected that environmental uncertainty fosters a greater propensity to adopt AI technologies.

Hypothesis 3: A positive association exists between EU and WA.

Willingness to adopt AI and Supply chain Resilience (SR)

Integrating digital technologies into the supply chain enhances firms' responsiveness to customer demands while ensuring operational efficiency (Khan et al., 2025). For example, AI, a crucial digital technology, excels in information processing, allowing it to adapt effectively and swiftly to evolving customer requirements and manage uncertainties within the supply chain. SR encompasses both proactive and reactive approaches that help companies navigate disruptions (Kumawat, 2024; Sharma et al., 2024). The primary aim of companies in developing resilient supply chains lies in their ability to rapidly recover from disruptions, mitigate adverse impacts, and maintain consistent and timely delivery of customer orders and services (Huang et al., 2023). AI can analyze vast amounts of data as a tool for information processing, while innovative decision-making driven by AI further bolsters SR (Zamani et al., 2022). Consequently, it is anticipated that the WA will positively influence the establishment of SR. Accordingly, this study puts forth the following hypothesis:

Hypothesis 4: A positive association exists between WA and SR.

Willingness to Adopt and Supply Chain Performance (SP)

AI-driven data analytics enhances supply chains by providing better insights and efficiencies. They allow companies to spot inefficiencies, boost productivity, and elevate customer satisfaction through insights derived from data (Lee et al., 2022). Additionally, research shows that AI analytics platforms offer real-time visibility, enabling firms to pinpoint bottlenecks and enhance their SP swiftly. This performance reflects how effectively a company manages its supply chain operations, particularly in minimizing costs and satisfying customer needs (Zamani et al., 2022; Wang & Pan, 2022). Given AI's substantial potential to assist businesses in addressing challenges such as selecting orders, managing client relations, predicting demand, and sourcing materials, its implementation is expected to have a positive effect on SP (Mahraz et al., 2022). Accordingly, the subsequent hypothesis is proposed:
Hypothesis 5: A positive association exists between WA and SP.

Supply chain resilience and Supply chain performance

SR contributes meaningfully to enhancing SP, particularly amid crisis situations exemplified by the COVID-19 pandemic. SR includes the abilities to prepare for, respond to, and recover from disruptions, helping supply chains maintain continuous flow and minimize negative impacts, thereby enhancing SP through indicators such as cost, customer service, and on-time delivery (Tseng & Kiang, 2025; Juan et al., 2022). Studies have shown that a lack of SR is a key reason behind poor SP, particularly during crises like COVID-19 (Gu et al., 2021; Qader et al., 2022). SR enables supply chains to maintain the continuous flow of materials, information, and finances, while mitigating the adverse effects of disruptions, thus improving SP through factors such as on-time delivery, customer satisfaction, and efficient cost management (Bahrami et al., 2022). Juan et al. (2022) pointed out that components of SR such as collaboration and flexibility have a direct impact on SP. Bahrami et al. (2022) further emphasized that SR not only directly enhances SP but also plays a mediating role by transforming capabilities such as big data analytics into superior performance. Based on this evidence, the following hypothesis can be proposed:
H6: SR has a positive impact on SP.

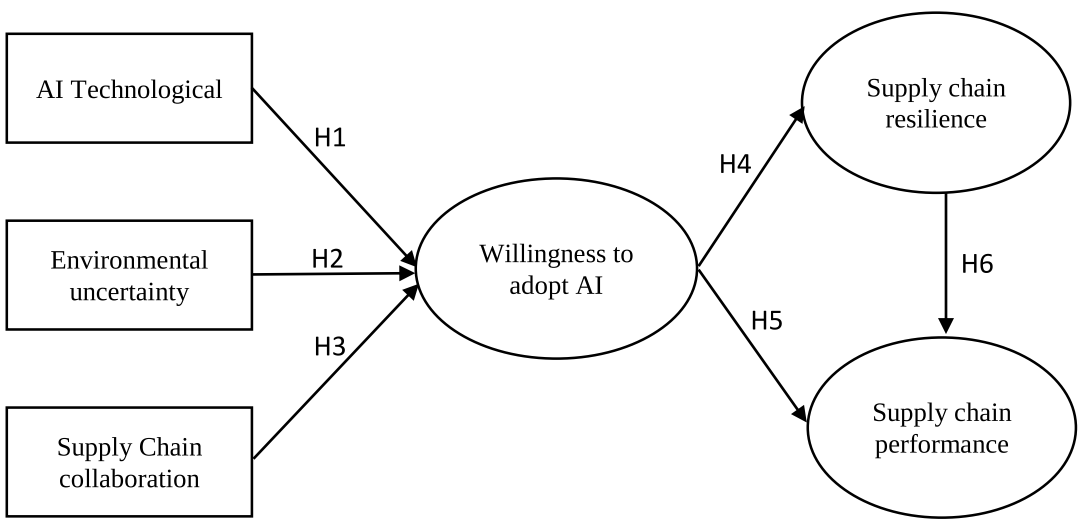

Figure 1. Proposed Research Model

3. Methodology

3.1. Sampling and Data Collection

To test the research hypotheses, the study conducted a survey targeting businesses engaged in agricultural activities within Vietnam's Mekong Delta area. This region is considered a suitable research setting to identify factors influencing the readiness to adopt AI in production activities, thereby clarifying the relationship between this readiness and the SR and operational efficiency of enterprises.

Amid climate change and the pressure for sustainable development, AI is being increasingly applied in the Mekong Delta, particularly in the fields of agriculture, water resources, and logistics. In drought forecasting, machine learning and deep learning approaches have shown enhanced predictive capabilities relative to conventional methods (Ha et al., 2024), supporting more effective agricultural planning and water resource allocation. In aquaculture, the integration of AI with GIS enables accurate prediction of common shrimp diseases, allowing farmers to make timely decisions (Khiem et al., 2022). Additionally, AI is being utilized in reverse logistics within the seafood sector to streamline transportation, resource recovery, and disposal processes, thereby enhancing operational performance and minimizing ecological footprints (Chuyen et al., 2024). However, implementation still faces several challenges, including high costs, limited human resources, and data constraints.

The number of active and tax-declared enterprises in the region totals approximately 70.6 thousand. The Mekong Delta has affirmed its position as Vietnam's leading hub for rice, seafood, and fruit production, contributing significantly to national food security and generating considerable foreign exchange earnings. The region produces 24.2 million tons of rice, accounting for 55.4% of the country's total rice output; 4.3 million tons of fruit, equivalent to 60% of the national production; and approximately 4.79 million tons of seafood, representing 55.7% of the nation's seafood output (Linh, 2025).

The study conducted surveys to collect data from provinces within the Mekong Delta region. The questionnaire was developed based on relevant academic literature and underwent a rigorous preparation process. Specifically, the research team consulted 12 experts, including researchers and business managers in the agricultural sector who are actively involved in implementing or applying AI technologies in their operations, to assess the content validity and relevance of the measurement scales used in the study. Prior to the official survey rollout, a pilot test was conducted with 30 business managers in the region to review and refine the questionnaire to ensure clarity and comprehensibility of the indicators. A total of 237 survey forms were administered, and after excluding 14 invalid responses, 223 valid questionnaires were retained for the final data analysis. Among the 223 participating enterprises, the majority (74.9%) had been operating for over 10 years, and 81.6% had fewer than 200 employees.

3.2. Variables and Measurement

All constructs, including both dependent and independent variables, were assessed through a five-point Likert scale comprising multiple items (1 = strongly disagree, 5 = strongly agree). AI Technological capability consisted of 6 items, adapted from the studies of Wang & Pan (2022); Vernier et al. (2021); Rugji et al. (2024); Nayal et al. (2021); and Lee et al. (2022). Environmental Uncertainty included 4 items designed based on the work of Wang & Pan (2022); Tseng & Kiang (2025); Liu et al. (2024); Ritambara et al. (2024); and Richey et al. (2023). Supply Chain Collaboration was measured with 4 items adapted from the studies of Wang & Pan (2022); Aghababaei et al. (2025); Nayal et al. (2021); and Khan et al. (2025). Willingness to Adopt AI comprised 5 items, developed based on theories and findings from Tseng & Kiang (2025); Liu et al. (2024); Mahraz et al. (2022); and Vishwakarma et al. (2024). Supply Chain Resilience was assessed with 5 items, established from the research of Kumawat (2024); Sharma et al. (2024); Huang et al. (2023); and Zamani et al. (2022). Supply Chain Performance consisted of 6 items, designed based on the studies of Tseng & Kiang (2025); Juan et al. (2022); Gu et al. (2021); Qader et al. (2022); and Bahrami et al. (2022).

4. Research Results

The consistency and reliability of the measurement framework were assessed by thoroughly examining key indicators, including factor loadings, average variance extracted (AVE), composite reliability (CR), and Cronbach's alpha (CA). According to the recommendations of Hair et al. (2021), a model is considered acceptable when factor loadings are at least 0.7, AVE exceeds 0.5, and both CR and CA are greater than 0.7.

The analysis results indicate that most indicators have factor loadings exceeding the 0.7 threshold, ranging from 0.889 (WA5) to 0.936 (EU4, SR5). However, two indicators (AT2 and SR1) did not meet the required criteria and were removed from the measurement model. This suggests that the retained items are strongly associated with their respective latent constructs, thereby confirming the adequacy of the measurement tools. Several indicators stood out with high loadings, including EU4 (0.936 – Innovation opportunities from the global business environment), SR5 (0.936 – Flexibility in handling issues), WA3 (0.932 – Application of AI technology), and AT3 (0.930 – AI enhances enterprise IT services). These results highlight the significance of these activities in measuring constructs related to AT, EU, SR, and WA (Table 2).
Data from Table 2 indicates that all variables in the model, including AT, EU, SC, WA, SR, and SP, exceed the minimum threshold values of 0.7 for both CA and CR. Specifically, CA values range from 0.940 (SC) to 0.964 (SP), indicating strong internal reliability across the measurement scales. Similarly, CR values fall between 0.957 (SC) and 0.971 (SP), confirming that the composite reliability of the scales fully meets the standard criteria. These results demonstrate that the constructed scales exhibit strong reliability and consistency, making them suitable for measuring the research constructs.

Table 2. Measurement model evaluation

Variables/Source	Indicators	Factor Loading	CA	CR	AVE	VIF
AI Technological (AT)	AT1	0.921	0.958	0.967	0.855	4.479
	AT3	0.930				4.605
	AT4	0.928				4.603
	AT5	0.919				4.255
	AT6	0.926				4.609
Environmental uncertainty (EU)	EU1	0.922	0.946	0.961	0.861	4.000
	EU2	0.930				4.111
	EU3	0.922				3.921
	EU4	0.936				4.674
Supply Chain collaboration (SC)	SC1	0.915	0.940	0.957	0.846	3.722
	SC2	0.923				3.896
	SC3	0.916				3.568
	SC4	0.926				3.840
Willingness to adopt AI (WA)	WA1	0.905	0.948	0.960	0.829	3.652
	WA2	0.918				4.089
	WA3	0.932				4.763
	WA4	0.907				3.780
	WA5	0.889				3.277
Supply chain resilience (SR)	SR2	0.926	0.946	0.961	0.861	4.061
	SR3	0.922				3.942
	SR4	0.928				3.980
	SR5	0.936				4.676
Supply chain performance (SP)	SP1	0.918	0.964	0.971	0.846	4.524
	SP2	0.922				4.690
	SP3	0.921				4.509
	SP4	0.920				4.554
	SP5	0.919				4.561
	SP6	0.921				4.779

The analysis results also show that the AVE values of all variables exceed the minimum acceptable level of 0.5, ranging from 0.829 for the WA variable to 0.861 for the EU and SR variables. This indicates that the indicators of each variable effectively reflect their respective latent constructs, thereby confirming the model's convergent validity. Notably, the variables WA (including indicators such as Willingness to experiment with AI; plan to adopt AI; have adopted AI; Intend to adopt AI) and SR (including indicators such as recovery of material flows; rapid restoration of operations; supply chain recovery; return to normal state; flexible incident handling) have the highest AVE scores (0.861), showing that these indicators clearly represent the constructs of WA and SR in this study.
In addition, all indicators have VIF values within the acceptable range, spanning from 3.277 (WA5) to 4.780 (WA4), remaining under the widely recognized cut-off point of 5.0. This suggests that multicollinearity among indicators

within the same variable or between latent variables is not a significant concern. However, some indicators related to WA, SP, and AI have relatively high VIF values, reflecting the likelihood that these indicators are closely related. This is reasonable given that AI implementation solutions in the agricultural sector of the Mekong Delta are often carried out in a synchronized manner and in coordination with one another.

Table 3 presents the indices used to evaluate the model fit, including SRMR, d_ULS, d_G, Chi-Square, and NFI, with a comparison between the Saturated Model (SM) and the Estimated Model (EM). The EM has an SRMR value of 0.044, which is below the commonly accepted threshold of 0.08 in SEM (Structural Equation Modeling) analysis, indicating that the difference between the empirical covariance matrix and the estimated covariance matrix is minimal, and thus the model is considered a good fit. Compared to the saturated model (SRMR = 0.033), the SRMR of the EM shows a slight increase, which is reasonable since saturated models often exhibit better fit due to the absence of structural constraints. The d_ULS index in the estimated model reaches 0.769, significantly higher than the value of 0.445 in the saturated model. This index measures the discrepancy between the two covariance matrices using the unweighted least squares method. Although the higher value indicates greater deviation between the model and the data, since there is no fixed threshold for this index, its evaluation should be conducted in conjunction with other indices. Regarding d_G, the estimated model achieves a value of 0.391, compared to 0.385 in the saturated model. This index reflects the geometric discrepancy between the actual data and the theoretical framework. These values are below 1 and fall within acceptable limits. The Chi-Square of the estimated model is 510.804, higher than that of the saturated model (503.785), which is common in complex models or those with large sample sizes, as this index tends to increase under such conditions. Finally, the NFI of the estimated model is 0.926, slightly lower than that of the saturated model (0.927). Both values exceed the threshold of 0.9, indicating a good model fit.

Table 3. Model Fit Analysis

	Saturated Model	Estimated Model
SRMR	0.033	0.044
d_ULS	0.445	0.769
d_G	0.385	0.391
Chi-Square	503.785	510.804
NFI	0.927	0.926

Based on the results of the Heterotrait-Monotrait Ratio (HTMT) analysis (Table 4), all values fall below the acceptable threshold of 0.85, ranging from 0.101 to 0.557. This indicates that the measurement model achieves discriminant validity among all pairs of latent variables. Specifically, no variable pair exceeds the threshold, demonstrating that the theoretical constructs measured are distinct and non-overlapping. Ensuring discriminant validity is a necessary condition for establishing the consistency and accuracy of constructs within the measurement framework in SEM. These findings align with the recommendation of Henseler et al. (2015), who assert that HTMT < 0.85 is a reliable indicator of discriminant validity. Thus, the research model has a robust measurement foundation, facilitating subsequent structural model testing and hypothesis evaluation.

Table 4. Heterotrait-Monotrait Ratio (HTMT)

	AT	EU	SC	SP	SR	WA
AT						
EU	0.274					
SC	0.344	0.408				
SP	0.101	0.239	0.200			
SR	0.254	0.298	0.309	0.476		
WA	0.462	0.481	0.557	0.441	0.486	

The results of the Fornell–Larcker criterion analysis (Table 5) indicate that the measurement model achieves discriminant validity among the latent variables. Specifically, the AVE of each variable (the values on the main diagonal) is greater than the correlation coefficients between that variable and the others in the model. For instance, values such as 0.925 (AT), 0.928 (EU), 0.920 (SC), 0.920 (SP), 0.928 (SR), and 0.910 (WA) all exceed their corresponding correlation coefficients. This demonstrates that the latent constructs in the study are conceptually distinct and non-overlapping. Thus, the results confirm the discriminant validity of the measurement variables, reinforcing the reliability and validity of the model and establishing a solid foundation for subsequent analyses within the structural model.

Table 5. Fornell-Larcker Criterion

	AT	EU	SC	SP	SR	WA
AT	0.925					
EU	0.261	0.928				
SC	0.329	0.384	0.920			
SP	0.099	0.229	0.192	0.920		
SR	0.244	0.283	0.291	0.456	0.928	
WA	0.442	0.457	0.526	0.423	0.460	0.910

The R Square results table (Table 6) illustrates the explanatory power of the independent variables for the three dependent variables in the model. Specifically, the variable SP has an R^2 value of 0.265 and an adjusted R^2 of 0.259, indicating that 26.5% of the variance in SP is explained by the variables in the model; this level is considered moderate and methodologically appropriate within the context of social science research. The variable SR has an R^2 of 0.212 and an adjusted R^2 of 0.208, reflecting a low explanatory power, yet still appropriate for complex behavioral models. Notably, the variable WA reaches an R^2 of 0.413 and an adjusted R^2 of 0.405, suggesting that the model provides a fairly good explanation for this variable. The small differences between R^2 and adjusted R^2 across all three variables indicate that the model is not affected by overfitting. Overall, these results indicate that the model possesses a suitable and reliable level of explanatory power, supporting the proposed research hypotheses.

Table 6. R Square

	R Square	R Square Adjusted
SP	0.265	0.259
SR	0.212	0.208
WA	0.413	0.405

The analysis results of the f^2 values in the model indicate the extent to which independent variables influence dependent variables. According to Cohen's (1988) standard, f^2 values are classified into small (0.02), medium (0.15), and large (0.35) effect sizes. In Table 7, the variable WA has a medium effect on SR with $f^2 = 0.269$, indicating that it is the most influential factor on SR within the model. Next, SC also shows a medium effect on WA with $f^2 = 0.158$. The two variables AT and EU have small effects on WA, at 0.103 and 0.093 respectively, suggesting that they play a supporting role in explaining the WA in enterprises. Additionally, SR and WA have small effects on SP, with values of $f^2 = 0.117$ and $f^2 = 0.079$, respectively. Overall, the f^2 results support the robustness of the proposed research model.

Table 7. F Square

	AT	EU	SC	SP	SR	WA
AT						0.103
EU						0.093
SC						0.158
SP						
SR				0.117		
WA				0.079	0.269	

According to the empirical evidence summarized in Table 8 and Figure 2 regarding the direct relationships between variables in the model, it can be observed that all hypotheses are accepted with p-values less than 0.05, indicating statistically significant relationships among the variables in the model. Specifically, the relationship between AT and WA has a T-value of 4.822 and a P-value of 0.000, demonstrating a strong influence of AI Technological on Willingness to adopt AI. Similarly, EU and SC also show a positive impact on WA with T-values of 4.378 and 6.697, respectively. The relationships between SR and SP, as well as from WA to SR, are confirmed with outstanding T-values (5.463 and 8.031). The small standard deviation (0.051–0.061) in these relationships indicates the consistency of the data. These results reflect the coherence among the factors and their strong inter impact, providing a solid foundation for developing sustainable strategies in SCM.

Table 8. Direct Relationships Between Variables in the Model

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values	Hypothesis Results
AT -> WA	0.263	0.265	0.055	4.822	**0.000**	H1 (Accepted)
EU -> WA	0.257	0.259	0.059	4.378	**0.000**	H2 (Accepted)
SC -> WA	0.341	0.339	0.051	6.697	**0.000**	H3 (Accepted)
SR -> SP	0.331	0.337	0.061	5.463	**0.000**	H4 (Accepted)
WA -> SP	0.271	0.270	0.060	4.482	**0.000**	H5 (Accepted)
WA -> SR	0.460	0.464	0.057	8.031	**0.000**	H6 (Accepted)

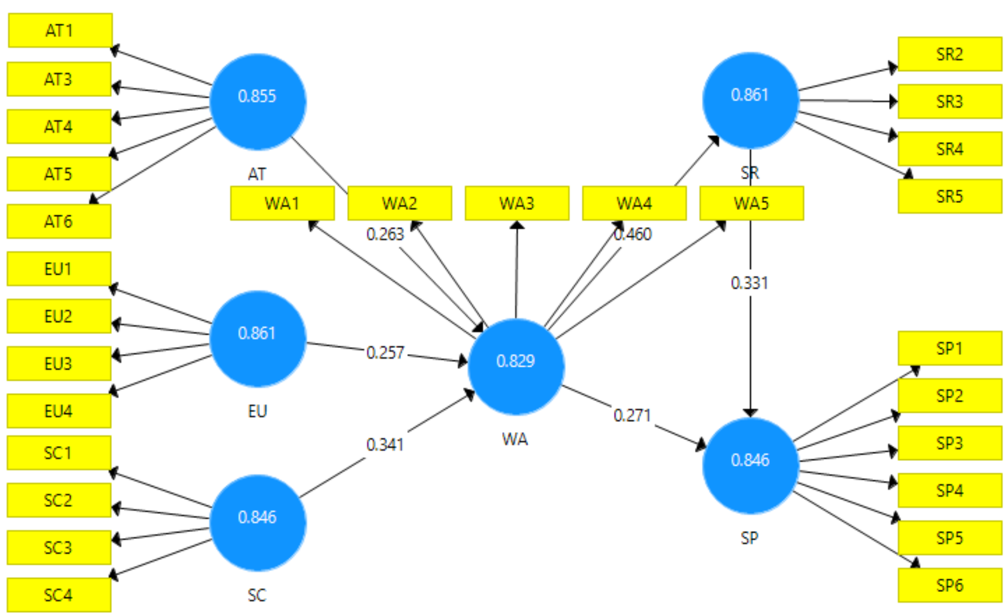

Figure 2. Results of SEM Model Analysis

The analysis results of the indirect relationships between variables in the model (Table 9) show that all mediating paths are statistically significant with p-values < 0.05. Notably, the indirect relationships SC → WA → SR and WA → SR → SP have the highest path coefficients, at 0.157 and 0.152 respectively, confirming the strong mediating role of SR in enhancing sustainable performance. In addition, other indirect paths such as AT → WA → SR → SP, EU → WA → SR → SP, and SC → WA → SR → SP also demonstrate positive effects, with SC showing the strongest impact. These findings highlight the crucial roles of WA and SR as key mediating variables in transmitting the influence of input factors, such as AI Technological, Environmental Uncertainty, and Supply Chain Collaboration, on Supply Chain Performance within the organization.

Table 9. Indirect Relationships Between Variables in the Model

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
AT -> WA -> SR -> SP	0.040	0.042	0.013	3.066	**0.002**
EU -> WA -> SR -> SP	0.039	0.041	0.014	2.779	**0.006**
WA -> SR -> SP	0.152	0.156	0.036	4.251	**0.000**
SC -> WA -> SR -> SP	0.052	0.053	0.014	3.620	**0.000**
AT -> WA -> SP	0.071	0.072	0.022	3.189	**0.002**
EU -> WA -> SP	0.070	0.070	0.023	3.059	**0.002**
SC -> WA -> SP	0.093	0.092	0.025	3.708	**0.000**
AT -> WA -> SR	0.121	0.123	0.031	3.911	**0.000**
EU -> WA -> SR	0.118	0.120	0.031	3.765	**0.000**
SC -> WA -> SR	0.157	0.157	0.031	5.095	**0.000**

5. Conclusion and Discussion

This study provides significant insights into the role of AI in enhancing SR and SP within agri-food firms in the Mekong Delta, Vietnam. The findings confirm all proposed hypotheses, demonstrating that AI technological compatibility, supply chain collaboration, and environmental uncertainty positively influence the willingness to adopt AI, thereby significantly improving SR and SP. Notably, the mediating role of SR in the relationship between WA and SP underscores its importance in translating technology adoption into tangible outcomes. These results align with prior studies highlighting AI's transformative potential in SCM (Tseng & Kiang, 2025; Sharma et al., 2024; Wang & Pan, 2022) and extend the literature by focusing on the under-explored agri-food sector in emerging markets.

The empirical results emphasize that AT (H1) strongly influences WA, confirming the TOE framework's focus on technological fit (Wang & Pan, 2022). This suggests that agri-food firms are more likely to adopt AI when it aligns with existing systems, reducing implementation barriers. SC (H2) emerges as the strongest driver of WA, with an f^2 value of 0.158, indicating that collaborative relationships foster a conducive environment for AI integration by enabling resource and information sharing (Aghababaei et al., 2025). EU (H3) also positively affects WA, reflecting firms' proactive responses to volatile market conditions through AI-based solutions (Ritambara et al., 2024). The strong relationship between WA and SR (H4, $f^2 = 0.269$) underscores AI's role in enhancing absorptive, adaptive, and restorative capacities, enabling firms to effectively mitigate disruptions (Kumawat, 2024). Furthermore, both WA (H5) and SR (H6) positively impact SP, with SR mediating the relationship between WA and SP, suggesting that resilience is a critical pathway for realizing AI's benefits in cost efficiency, customer responsiveness, and operational flexibility (Bahrami et al., 2022; Juan et al., 2022).

The study's findings offer several practical implications for agri-food firms, policymakers, and supply chain stakeholders in emerging economies. First, firms should prioritize investing in AI technologies compatible with existing infrastructure to minimize adoption barriers and maximize operational benefits. For instance, AI applications such as machine learning for demand forecasting or IoT-based crop monitoring can enhance efficiency and resilience, as demonstrated in agricultural activities in the Mekong Delta (Ha et al., 2024; Khiem et al., 2022). Second, fostering supply chain collaboration through partnerships and information-sharing platforms can accelerate AI adoption, as collaborative networks reduce risks and enhance resource access. Policymakers and development agencies should support this by providing incentives for digital infrastructure development and training programs to address the region's digital capability constraints and high implementation costs (Kalimuthu et al., 2024). Third, the mediating role of SR suggests that firms should integrate AI into resilience-building strategies, such as real-time risk monitoring and predictive analytics, to ensure sustainable performance amid disruptions like climate change or market volatility, which are prevalent in the Mekong Delta (Linh, 2025).

The Mekong Delta in Vietnam faces fragmented logistics and severe climate change impacts, such as flooding and salinization, increasing the vulnerability of agricultural supply chains (Linh, 2025). Similarly, India grapples with poor logistical infrastructure and climate instability, such as droughts and floods (Kalimuthu et al., 2024), while Brazil faces challenges from vast geographical distances and uncoordinated transport systems, escalating costs (Cicerelli & Ravetti, 2024). However, Brazil has larger firms with superior capital and technology, unlike the resource-constrained SMEs in the Mekong Delta (Kalimuthu et al., 2024). The finding regarding the role of supply chain collaboration in driving AI adoption (H2) is generalizable across emerging markets, as resource sharing is critical (Aghababaei et al., 2025). For instance, farmer cooperatives in India promote digital technology adoption, similar to those in the Mekong Delta (Pandey & Mishra, 2024). However, the impact of environmental uncertainty (H3) is more specific to the Mekong Delta due to urgent climate-related threats (Ha et al., 2024), whereas Brazil, with more stable policies, is less affected by this factor (Cicerelli & Ravetti, 2024).

In conclusion, this study advances the understanding of AI's role in enhancing SR and SP within the agri-food sector of an emerging economy. By integrating the TOE framework with the RBV and behavioral constructs, the study provides a robust model for analyzing AI adoption and its outcomes. The findings offer practical guidance for stakeholders to leverage AI to manage the intricate dynamics of contemporary supply chains, particularly in regions facing significant environmental and logistical challenges. Overcoming the noted constraints and advancing the suggested research pathways will further strengthen the theoretical and practical contributions of this field

6. Research Implications

This study highlights the significant capacity of AI to improve SR and SP within the agri-food sector of the Mekong Delta, Vietnam. By integrating the TOE framework with the RBV and behavioral constructs, it confirms that AI technological compatibility, supply chain collaboration, and environmental uncertainty drive AI adoption willingness, significantly improving SR and SP. The research fills a gap by focusing on the agri-food sector in emerging economies, contrasting with prior studies on high-tech industries (Cicerelli & Ravetti, 2024). The mediating role of SR in linking AI adoption to SP underscores resilience as a key pathway for operational success, aligning with findings from Bahrami et al. (2022) and Juan et al. (2022).

For agri-food firms, prioritizing AI technologies compatible with existing infrastructure, such as machine learning for demand forecasting or IoT-based crop monitoring, minimizes adoption barriers. Supply chain collaboration, the strongest driver of AI adoption, fosters integration through resource and information sharing. Environmental uncertainty encourages proactive AI adoption to mitigate market volatility, enhancing competitiveness in dynamic settings like the Mekong Delta.

Policymakers should tackle barriers like high costs and limited digital infrastructure with incentives, training, and subsidies to support SMEs. Integrating AI into resilience strategies, such as real-time risk monitoring and predictive analytics, ensures sustainable performance amid environmental and logistical challenges. Addressing confidentiality concerns and biases within algorithms further promotes equitable AI adoption, enhancing food security and economic sustainability. Taken together, the results suggest practical avenues for advancing SDG 9, SDG 12, and SDG 13 via targeted investments in data and AI capabilities and by strengthening collaboration across supply chain actors (SDG 17), while supporting inclusive productivity improvements consistent with SDG 8.

The mechanisms identified here remain relevant in times of crisis. In particular, building data and AI capabilities and strengthening collaboration among supply chain actors can support continuity of operations, faster reconfiguration of procurement and logistics, and recovery of service levels. These organizational levers complement crisis specific planning approaches documented for pandemic and wartime settings and help translate strategic plans into day to day execution at the firm level (Rahbari et al., 2024, 2025a, 2025b).

7. Limitations and Recommendations

Despite its contributions, this study has limitations to consider. First, the research is confined to the Mekong Delta, which, although representative of emerging economies, may not fully reflect the diversity of challenges in other regions or industries. Future studies could expand the geographical scope to include other emerging markets or compare agri-food supply chains with other sectors, such as electronics or automotive, to enhance generalizability (Cicerelli & Ravetti, 2024). Second, the study utilizes cross-sectional survey data, restricting its capacity to observe the evolving, longitudinal impacts of AI adoption on SR and SP. Longitudinal studies could provide deeper insights into how AI capabilities evolve over time and their long-term impacts on supply chain outcomes. Third, the study

does not explore specific AI technologies (e.g., machine learning, computer vision) or their differential impacts, which could be a valuable direction for future research (Jackson et al., & 2024). Additionally, barriers such as data privacy, algorithmic bias, and limited digital infrastructure, noted as challenges in emerging markets (Pandey & Mishra, 2024), were not quantitatively assessed in this study and require further exploration. Because the sample was not collected during an acute crisis, external validity to war or pandemic conditions should be tested directly, for example by combining our adoption to outcome model with crisis specific scenarios as in recent robust and stochastic formulations (Rahbari et al., 2024; 2025a).
Future research directions include examining the role of specific AI applications, such as generative AI or robotics, in enhancing SR and SP within the agri-food context. Additionally, future studies can employ artificial intelligence in mathematical modeling of agri food supply chains, for example by using machine learning for demand and yield forecasting, reinforcement learning and simulation for dynamic inventory, routing and capacity decisions, and hybrid AI with stochastic or robust optimization for network design and policy evaluation under uncertainty. Exploring the interaction among organizational culture, leadership, and willingness to adopt AI could provide deeper insights into behavioral factors affecting technology integration (Nayal et al., 2021). Moreover, exploring the cost-benefit dynamics of AI implementation in resource-constrained environments could provide practical insights for small and medium-sized enterprises, which predominate in the Mekong Delta's agri-food sector (Khan et al., 2025). Finally, integrating additional theoretical lenses, such as institutional theory or dynamic capabilities, could enrich the conceptual framework by considering regulatory and competitive dynamics in emerging markets.

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References

Aghababaei, A., Aghababaei, F., Pignitter, M., & Hadidi, M. (2025). Artificial Intelligence in agro-food systems: From farm to fork. *Foods*, 14(3), 411. https://doi.org/10.3390/foods14030411

Ahmad, A., Liew, A. X., Venturini, F., Kalogeras, A., Candiani, A., Di Benedetto, G., Ajibola, S., Cartujo, P., Romero, P., Lykoudi, A., De Grandis, M. M., Xouris, C., Lo Bianco, R., Doddy, I., Elegbede, I., D'Urso Labate, G. F., García del Moral, L. F., & Martos, V. (2024). AI can empower agriculture for Global Food Security: Challenges and prospects in developing nations. *Frontiers in Artificial Intelligence*, 7. https://doi.org/10.3389/frai.2024.1328530

Al Hadwer, A., Tavana, M., Gillis, D., & Rezania, D. (2021). A systematic review of organizational factors impacting cloud-based technology adoption using technology-organization-environment framework. *Internet of Things*, 15. https://doi.org/10.1016/j.iot.2021.100407

Bačiulienė, V., Bilan, Y., Navickas, V., & Civín, L. (2023). The aspects of artificial intelligence in different phases of the food value and Supply Chain. *Foods*, 12(8), 1654. https://doi.org/10.3390/foods12081654

Bahrami, M., Shokouhyar, S., & Seifian, A. (2022). Big data analytics capability and supply chain performance: the mediating roles of supply chain resilience and innovation. *Modern Supply Chain Research and Applications*, 4(1), 62-84. https://doi.org/10.1108/MSCRA-11-2021-0021

Barney, J. (1991). Firm resources and sustained competitive advantage. *Journal of management*, 17(1), 99-120. https://doi.org/10.1177/014920639101700108

Biazar, S. M., Golmohammadi, G., Nedhunuri, R. R., Shaghaghi, S., & Mohammadi, K. (2025). Artificial Intelligence in hydrology: Advancements in soil, water resource management, and Sustainable Development. *Sustainability*, 17(5), 2250. https://doi.org/10.3390/su17052250

Bran, F., Alexandru Bodislav, D., Gombos, S., & Petrică Angheluță, S. (2024). Artificial Intelligence for Sustainable Agribusiness: Innovations and challenges. *European Journal of Sustainable Development*, 13(3), 233. https://doi.org/10.14207/ejsd.2024.v13n3p233

Bromiley, P., & Rau, D. (2016). Operations management and the resource based view: Another view. *Journal of operations management*, 41, 95-106. https://doi.org/10.1016/j.jom.2015.11.003

Cannas, V. G., Ciano, M. P., Saltalamacchia, M., & Secchi, R. (2023). Artificial Intelligence in Supply Chain and Operations Management: A multiple case study research. *International Journal of Production Research*, 62(9), 3333–3360. https://doi.org/10.1080/00207543.2023.2232050

Chittipaka, V., Kumar, S., Sivarajah, U., Bowden, J. L. H., & Baral, M. M. (2023). Blockchain Technology for Supply Chains operating in emerging markets: an empirical examination of technology-organization-environment (TOE) framework. *Annals of Operations Research*, 327(1), 465-492. https://doi.org/10.1007/s10479-022-04801-5

Chui, M., Hazan, E., Roberts, R., Singla, A., Smaje, K., Sukharevsky, A., Yee, L., & Zemmel, R. (2023). The economic potential of Generative AI: The Next Productivity Frontier. *McKinsey & Company*. https://www.mckinsey.com/capabilities/mckinsey-digital/our-insights/the-economic-potential-of-generative-ai-the-next-productivity-frontier

Chuyen, T. T., Trinh, P. T. X., & Huy T. T. (2024). Application of artificial intelligence in reverse logistics: A case study of seafood enterprises in the Mekong Delta. *In 7.1 International Conference on Digital Innovation - Sustainability Through the Lens of Sustainable Development Goals (SDG)*, pp. 487–495.

Cicerelli, F., & Ravetti, C. (2024). Sustainability, resilience and innovation in industrial electronics: a case study of internal, supply chain and external complexity. *Journal of Economic Interaction and Coordination*, 19(2), 343-372. https://doi.org/10.1007/s11403-023-00396-7

Clulow, V., Barry, C., & Gerstman, J. (2007). The resource-based view and value: the customer-based view of the firm. *Journal of European industrial training*, 31(1), 19-35. https://doi.org/10.1108/03090590710721718

Cohen, J. W. (1988). Statistical power analysis for the behavioral sciences. *Lawrence ErlbaumAssociates, Hillsdale, NJ*. https://doi.org/10.4324/9780203771587

Cruz, L., & Ignacio, P. S. D. A. (2023). Application of blockchain disruptive technology in agri-food chains for sustainable development, a systematic review. *International Journal of Supply and Operations Management*, 10(4), 523-544. 10.22034/IJSOM.2023.110040.2837

Dai, J., Geng, R., Xu, D., Shangguan, W., & Shao, J. (2024). Unveiling the impact of the congruence between artificial intelligence and explorative learning on supply chain resilience. *International Journal of Operations & Production Management*, 45(2), 570-593. https://doi.org/10.1108/IJOPM-12-2023-0990

El Bhilat, E. M., El Jaouhari, A., & Hamidi, L. S. (2024). Assessing the influence of artificial intelligence on Agri-Food Supply Chain Performance: The mediating effect of distribution network efficiency. *Technological Forecasting and Social Change*, 200, 123149. https://doi.org/10.1016/j.techfore.2023.123149

El Jaouhari, A., & Hamidi, L. S. (2024). Assessing the influence of artificial intelligence on agri-food supply chain performance: the mediating effect of distribution network efficiency. *Technological Forecasting and Social Change*, 200. https://doi.org/10.1016/j.techfore.2023.123149

Feng, Y., Mei, D., & Zhao, H. (2023). Auction-based deep learning-driven smart agricultural supply chain mechanism. *Applied Soft Computing*, 149, 111009. https://doi.org/10.1016/j.asoc.2023.111009

Food Security Information Network (FSIN). (2024). *Global Report on Food Crises 2024*. https://www.wfp.org/publications/global-report-food-crises-grfc

Gu, M., Yang, L., & Huo, B. (2021). The impact of information technology usage on supply chain resilience and performance: An ambidexterous view. *International journal of production economics*, 232. https://doi.org/10.1016/j.ijpe.2020.107956

Gupta, S., Modgil, S., Meissonier, R., & Dwivedi, Y. K. (2024). Artificial Intelligence and Information System Resilience to cope with supply chain disruption. *IEEE Transactions on Engineering Management*, 71, 10496–10506. https://doi.org/10.1109/tem.2021.3116770

Ha, D. H., Duc, P. N., Luong, T. H., Duc, T. T., Ngoc, T. T., Minh, T. N., & Minh, T. N. (2024). Application of Artificial Intelligence to Forecast Drought Index for the Mekong Delta. *Applied Sciences*, 14(15), 6763. https://doi.org/10.3390/app14156763

Hendriksen, C. (2023). Artificial Intelligence for Supply Chain Management: Disruptive innovation or innovative disruption? *Journal of Supply Chain Management*, 59(3), 65–76. https://doi.org/10.1111/jscm.12304

Huang, K., Wang, K., Lee, P. K. C., & Yeung, A. C. L. (2023). The impact of Industry 4.0 on supply chain capability and Supply Chain Resilience: A dynamic resource-based view. *International Journal of Production Economics*, 262, 108913. https://doi.org/10.1016/j.ijpe.2023.108913

Jackson, I., Ivanov, D., Dolgui, A., & Namdar, J. (2024). Generative Artificial Intelligence in Supply Chain and Operations Management: A capability-based framework for analysis and implementation. *International Journal of Production Research*, 62(17), 6120–6145. https://doi.org/10.1080/00207543.2024.2309309

Juan, S. J., Li, E. Y., & Hung, W. H. (2022). An integrated model of supply chain resilience and its impact on supply chain performance under disruption. *The International Journal of Logistics Management*, 33(1), 339-364. https://doi.org/10.1108/IJLM-03-2021-0174

Jung, J., Maeda, M., Chang, A., Bhandari, M., Ashapure, A., & Landivar-Bowles, J. (2021). The potential of remote sensing and artificial intelligence as tools to improve the resilience of Agriculture Production Systems. *Current Opinion in Biotechnology*, 70, 15–22. https://doi.org/10.1016/j.copbio.2020.09.003

Kalimuthu, T., Kalpana, P., Kuppusamy, S., & Raja Sreedharan, V. (2024). Intelligent decision-making framework for Agriculture Supply Chain in emerging economies: Research opportunities and challenges. *Computers and Electronics in Agriculture*, 219, 108766. https://doi.org/10.1016/j.compag.2024.108766

Khan, S. A., Sheikh, A. A., Shamsi, I. R., & Yu, Z. (2025). The implications of artificial intelligence for small and medium-sized enterprises' sustainable development in the areas of blockchain technology, Supply Chain Resilience, and closed-loop supply chains. *Sustainability*, 17(1), 334. https://doi.org/10.3390/su17010334

Khiem, N. M., Takahashi, Y., Yasuma, H., Oanh, D. T. H., Hai, T. N., Ut, V. N., & Kimura, N. (2022). Use of GIS and machine learning to predict disease in shrimp farmed on the east coast of the Mekong Delta, Vietnam. *Fisheries science*, 1-13. https://doi.org/10.1007/s12562-021-01577-8

Kumawat, P. (2024). Impact of artificial intelligence in Building Supply Chain resiliency. *International Journal of Supply Chain Management*, 13(6), 10–20. https://doi.org/10.59160/ijscm.v13i6.6283

Lee, K. L., Azmi, N. A., Hanaysha, J. R., Alzoubi, H. M., & Alshurideh, M. T. (2022). The effect of digital supply chain on organizational performance: An empirical study in malaysia manufacturing industry. *Uncertain Supply Chain Management*, 10(2), 495–510. https://doi.org/10.5267/j.uscm.2021.12.002

Linh, T. (2025). The localities in the Mekong Delta region make a significant contribution to the socio-economic development of the entire country. *The Ministry of Planning and Investment of Vietnam*. Retrieved from https://www.mpi.gov.vn/portal/Pages/2025-1-3/Cac-dia-phuong-trong-vung-Dong-bang-song-Cuu-Long-pww99c.aspx

Liu, Yansui, Huang, X., & Liu, Y. (2024). Detection of long-term land use and ecosystem services dynamics in the Loess Hilly-Gully region based on Artificial Intelligence and multiple models. *Journal of Cleaner Production*, 447, 141560. https://doi.org/10.1016/j.jclepro.2024.141560

Liu, Yong, Wang, H., Zhang, H., & Liber, K. (2016). A comprehensive support vector machine-based classification model for Soil Quality Assessment. *Soil and Tillage Research*, 155, 19–26. https://doi.org/10.1016/j.still.2015.07.006

Liu, Z., Costa, C., & Wu, Y. (2024). Leveraging data-driven insights to enhance supplier performance and Supply Chain Resilience. *World Journal of Innovation and Modern Technology*, 7(5), 125–131. https://doi.org/10.53469/wjimt.2024.07(05).15

Lockett, A., & Thompson, S. (2001). The resource-based view and economics. *Journal of management*, 27(6), 723-754. https://doi.org/10.1016/S0149-2063(01)00121-0

Lockett, A., Thompson, S., & Morgenstern, U. (2009). The development of the resource-based view of the firm: A critical appraisal. *International journal of management reviews*, 11(1), 9-28. https://doi.org/10.1111/j.1468-2370.2008.00252.x

Mahraz, M.-I., Benabbou, L., & Berrado, A. (2022). Machine Learning in Supply Chain Management: A Systematic Literature Review. *International Journal of Supply and Operations Management,* 9(4), 398–416. https://doi.org/10.22034/ijsom.2021.109189.2279

Misra, N. N., Dixit, Y., Al-Mallahi, A., Bhullar, M. S., Upadhyay, R., & Martynenko, A. (2022). IOT, Big Data, and artificial intelligence in agriculture and Food Industry. *IEEE Internet of Things Journal*, 9(9), 6305–6324. https://doi.org/10.1109/jiot.2020.2998584

Muhammed, D., Ahvar, E., Ahvar, S., Trocan, M., Montpetit, M.-J., & Ehsani, R. (2024). Artificial Intelligence of Things (AIOT) for Smart Agriculture: A Review of Architectures, technologies and solutions. *Journal of Network and Computer Applications*, 228, 103905. https://doi.org/10.1016/j.jnca.2024.103905

Nayal, K., Raut, R., Priyadarshinee, P., Narkhede, B. E., Kazancoglu, Y., & Narwane, V. (2021). Exploring the role of artificial intelligence in managing agricultural supply chain risk to counter the impacts of the covid-19 pandemic. *The International Journal of Logistics Management*, 33(3), 744–772. https://doi.org/10.1108/ijlm-12-2020-0493

Nguyen, T. H., Le, X. C., & Vu, T. H. L. (2022). An extended technology-organization-environment (TOE) framework for online retailing utilization in digital transformation: Empirical evidence from Vietnam. *Journal of Open Innovation: Technology, Market, and Complexity,* 8(4). https://doi.org/10.3390/joitmc8040200

Nwamekwe, C. O., & Igbokwe, N. C. (2024). Supply Chain Risk Management: Leveraging AI for Risk Identification, mitigation, and Resilience Planning. *International Journal of Industrial Engineering, Technology & Operations Management*, 2(2), 41–51. https://doi.org/10.62157/ijietom.v2i2.38

Pandey, D. K., & Mishra, R. (2024). Towards sustainable agriculture: Harnessing AI for Global Food Security. *Artificial Intelligence in Agriculture*, 12, 72–84. https://doi.org/10.1016/j.aiia.2024.04.003

Patalas-Maliszewska, J., Szmołda, M., & Łosyk, H. (2024). Integrating artificial intelligence into the supply chain in order to enhance sustainable production—a systematic literature review. *Sustainability*, 16(16), 7110. https://doi.org/10.3390/su16167110

Peggy M.L. Ng., Lit, K. K., & Cheung, C. T. (2022). Remote work as a new normal? The technology-organization-environment (TOE) context. *Technology in Society*, 70. https://doi.org/10.1016/j.techsoc.2022.102022

Qader, G., Junaid, M., Abbas, Q., & Mubarik, M. S. (2022). Industry 4.0 enables supply chain resilience and supply chain performance. *Technological Forecasting and Social Change*, 185. https://doi.org/10.1016/j.techfore.2022.122026

Rahbari, M., Arshadi Khamseh, A., & Mohammadi, M. (2024). A novel robust probabilistic chance constrained programming and strategic analysis for Agri-food closed-loop supply chain under pandemic crisis. *Soft Computing*, *28*(2), 1179–1214. https://doi.org/10.1007/s00500-023-09156-y

Rahbari, M., Khamseh, A. A., & Mohammadi, M. (2025a). A multi-objective robust scenario-based stochastic chance constrained programming model for sustainable closed-loop agri-food supply chain. *Computers & Chemical Engineering*, *194*. https://doi.org/10.1016/j.compchemeng.2024.108914

Rahbari, M., Tavakkoli-Moghaddam, R., Razavi Hajiagha, S. H., & Jafari, M. J. (2025b). Wheat Supply Chain Network Design: Lesson for Resilience and Sustainability in a Situation of War and Crisis. *Journal of the Knowledge Economy*, 1–45. https://doi.org/10.1007/s13132-025-02682-0

Riad, M., Naimi, M., & Okar, C. (2024). Enhancing supply chain resilience through artificial intelligence: Developing a comprehensive conceptual framework for AI implementation and supply chain optimization. *Logistics*, 8(4), 111. https://doi.org/10.3390/logistics8040111

Richey, R. G., Chowdhury, S., Davis-Sramek, B., Giannakis, M., & Dwivedi, Y. K. (2023). Artificial Intelligence in logistics and Supply Chain Management: A Primer and roadmap for research. *Journal of Business Logistics*, 44(4), 532–549. https://doi.org/10.1111/jbl.12364

Ritambara, Kaushal, S., & Shubham. (2024). Frontiers of Artificial Intelligence in agricultural sector: Trends and transformations. *Journal of Scientific Research and Reports*, 30(10), 970–980. https://doi.org/10.9734/jsrr/2024/v30i102518

Rugji, J., Erol, Z., Taşçı, F., Musa, L., Hamadani, A., Gündemir, M. G., Karalliu, E., & Siddiqui, S. A. (2024). Utilization of ai – reshaping the future of food safety, agriculture and Food Security – A critical review. *Critical Reviews in Food Science and Nutrition*, 1–45. https://doi.org/10.1080/10408398.2024.2430749

Sharifmousavi, M., Kayvanfar, V., & Baldacci, R. (2024). Distributed Artificial Intelligence Application in Agri-Food Supply Chains 4.0. *Procedia Computer Science*, 232, 211–220. https://doi.org/10.1016/j.procs.2024.01.021

Sharma, P., Gunasekaran, A., & Subramanian, G. (2024). Enhancing supply chain: Exploring and exploiting AI capabilities. *Journal of Computer Information Systems*, 1–15. https://doi.org/10.1080/08874417.2024.2386527

Singh, D., Sharma, A., Singh, R. K., & Rana, P. S. (2024). Augmenting supply chain resilience through AI and Big Data. *Business Process Management Journal*, 31(2), 631–657. https://doi.org/10.1108/bpmj-04-2024-0260

Singh, G., Sangeeta, K., Sharma, Y. K., Kothapalli, B., Bhanushali, M. M., Sanjeev, G., & Mircetic, D. (2025). Evaluating the Application of Blockchain for Electronics Supply Chain Traceability. *In Recent Trends In Engineering and Science for Resource Optimization and Sustainable Development* (pp. 10-13). CRC Press.

Singh, R. K., Modgil, S., & Shore, A. (2023). Building Artificial Intelligence Enabled Resilient Supply Chain: A multi-method approach. *Journal of Enterprise Information Management*, 37(2), 414–436. https://doi.org/10.1108/jeim-09-2022-0326

Tornatzky, L.G.; Fleischer, M.; Chakrabarti, A.K. (1990). Processes of Technological Innovation. *Lexington Books: Blue Ridge Summit, PA, USA*

Tseng, C. J., & Kiang, Y. J. (2025). Optimizing Supply Chain Sustainability through AI-Driven Policies and Integrator Facility. *International Journal of Supply & Operations Management*, 12(1). https://doi.org/10.22034/ijsom.2024.110137.2911

Vadlamudi, S. (2019). Agri-Food System and artificial intelligence: Reconsidering imperishability. *Asian Journal of Applied Science and Engineering*, 7(1), 33–42. https://doi.org/10.18034/ajase.v7i1.44

Vernier, C., Loeillet, D., Thomopoulos, R., & Macombe, C. (2021). Adoption of icts in Agri-Food Logistics: Potential and limitations for Supply Chain Sustainability. *Sustainability*, 13(12), 6702. https://doi.org/10.3390/su13126702

Vishwakarma, L. P., Singh, R. K., Mishra, R., & Venkatesh, M. (2024). Exploring the motivations behind artificial intelligence adoption for Building Resilient Supply Chains: A systematic literature review and future research agenda. *Journal of Enterprise Information Management*, 37(4), 1374–1398. https://doi.org/10.1108/jeim-11-2023-0606

Wang, M., & Pan, X. (2022). Drivers of Artificial Intelligence and their effects on Supply Chain Resilience and performance: An empirical analysis on an emerging market. *Sustainability*, 14(24), 16836. https://doi.org/10.3390/su142416836

Zamani, E. D., Smyth, C., Gupta, S., & Dennehy, D. (2022). Artificial Intelligence and big data analytics for supply chain resilience: A systematic literature review. *Annals of Operations Research*, 327(2), 605–632. https://doi.org/10.1007/s10479-022-04983-y