International Journal for Multidisciplinary Research (IJFMR)

E-ISSN: 2582-2160 ● Website: www.ijfmr.com ● Email: editor@ijfmr.com

From AI Adoption to Resilient Supply Chains: The Roles of Supplier Risk Sensing and Cybersecurity Readiness in Sustainable Supply Chain Performance in Ghana

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Abstract

This study examined how artificial intelligence adoption contributes to sustainable supply chain performance through supplier risk sensing and supply chain resilience, while considering the moderating role of cybersecurity readiness. A quantitative explanatory cross-sectional design was adopted. The data from respondents, representing 286 procurement, logistics, operations, risk-management and information-technology professionals from manufacturing, agro-processing, retail, pharmaceutical and logistics firms in Ghana was analysed. Data were modelled using partial least squares structural equation modelling with 5,000 bootstrap samples. The findings showed that artificial intelligence adoption had a significant positive effect on supplier risk sensing. Supplier risk sensing also improved supply chain resilience, while resilience positively influenced sustainable supply chain performance. Artificial intelligence retained a smaller direct effect on sustainable performance, indicating partial mediation. The sequential indirect relationship from artificial intelligence adoption through supplier risk sensing and resilience to sustainable supply chain performance was statistically significant. Cybersecurity readiness strengthened the relationship between artificial intelligence adoption and supplier risk sensing, showing that firms gain more value from AI-supported analytics when digital systems, data and third-party connections are adequately protected. The study concludes that AI adoption alone does not create sustainable and resilient supply chains. Firms must develop the organisational ability to interpret supplier risk signals, respond to disruptions and secure the digital infrastructure supporting supply chain decisions.

Keywords: artificial intelligence adoption; supplier risk sensing; cybersecurity readiness; supply chain resilience; sustainable supply chain performance; Ghana

1. Introduction

Supply chains are increasingly exposed to disruptions that originate from supplier failure, logistics interruptions, geopolitical conflict, climate events, infrastructure deficiencies, cyberattacks and sudden changes in demand (C. López et al., 2025; Qazi, 2025; Ivanov & Dolgui, 2020). These risks are difficult to manage because supply networks frequently extend across several tiers, while firms often have limited visibility beyond their immediate suppliers (Delgado et al., 2025). Supply chain resilience therefore concerns more than returning operations to their previous state after a disruption. It includes the capacity to anticipate threats, absorb shocks, adapt operations and reconfigure relationships when previous arrangements are no longer viable (Aniwa, 2026).. Artificial intelligence offers firms new ways of managing this uncertainty. In supply chain management, AI includes machine learning, predictive analytics, automated decision systems, natural-language processing and intelligent optimisation (Balan et al., 2025). These tools are used for demand forecasting, inventory planning, supplier evaluation, transport routing, production scheduling and disruption monitoring. AI can process large volumes of structured and unstructured information more quickly than conventional manual systems, enabling firms to detect patterns that may indicate delays, quality deterioration, capacity problems or financial distress among suppliers (Soori et al., 2024; Theodorakopoulos & Theodoropoulou, 2026).

Recent empirical evidence suggests that AI adoption can improve supply chain resilience. Tang et al. (2025) found that AI strengthened resilience across preparation, response and recovery by reducing dependence, supporting continuity and improving operational efficiency(Tang et al., 2025). Modgil et al. (2022) similarly showed that AI can support supply chain preparedness and response by improving information processing and decision-making (Modgil et al., 2021). A recent study of manufacturing SMEs also found that resilience mediated important parts of the relationship between AI capabilities and sustainability outcomes, suggesting that technological investment must first stabilise operations before wider benefits emerge (Ratanacharoenchai & Jantapoon, 2026).

The final outcome considered in the study is sustainable supply chain performance. This construct combines economic, environmental and social outcomes. Economic performance includes cost control, timely delivery, service continuity and efficient inventory use (Silva et al., 2025). Environmental performance concerns waste, resource consumption, emissions and environmentally responsible sourcing (Mugoni et al., 2024). Social performance includes labour standards, supplier welfare, safety and responsible relationships. Sustainable supply chain management requires firms to integrate these dimensions rather than treat short-term financial performance as the only relevant result (Fernando et al., 2022).

AI may contribute to sustainability through more accurate forecasting, reduced overproduction, optimised transportation, lower waste and improved supplier monitoring (Wang, 2026). These effects, however, are not automatic. AI systems can generate poor decisions when their data are incomplete, biased, manipulated or outdated. Excessive dependence on automated outputs may also weaken managerial judgement. Culot et al. (2024) caution that the empirical benefits of AI depend on data quality, organisational integration and implementation conditions rather than the mere acquisition of technology. Cybersecurity readiness is especially important because AI-supported supply chains depend on connected systems and the exchange of sensitive information among firms, suppliers and logistics providers (Culot et al., 2024). A breach affecting one partner may interrupt information, financial and physical flows across the network. Cybersecurity readiness includes access controls, data protection, employee awareness, supplier security assessments, system backups and incident-response arrangements. Herburger et al. (2024) found that cyber-resilient supply chains require specialised sensing, seizing and transforming capabilities, including cyber-risk knowledge, supply chain visibility and threat intelligence (Herburger et al., 2024).

The Ghanaian context makes these relationships worth examining. Ghana’s National Artificial Intelligence Strategy 2025–2035 identifies AI adoption in productive sectors, digital infrastructure, data governance, skills development and responsible deployment among the country’s policy priorities (Ministry of Interior , 2026). This creates opportunities for firms to introduce AI into procurement, manufacturing, logistics and supplier management. Yet Ghanaian firms continue to operate under infrastructure and capability constraints. A World Bank firm-level technology survey reported that 97%

of sampled Ghanaian firms experienced power outages, with a median of 13 outages per month, indicating the operating instability within which digital technologies are being introduced (Mwangi, 2026).
Cyber risks add another layer of uncertainty. Firms adopting AI without corresponding cybersecurity arrangements may consequently increase the number of digital entry points available to attackers (Kamya, 2025). Existing studies provide useful evidence on AI and resilience, but several gaps remain. First, much of the empirical work has been conducted in China, Europe and other technologically advanced or industrialised settings (Modgil et al., 2022; Tang et al., 2025). Second, studies often examine the direct relationship between AI and resilience without isolating supplier risk sensing as the mechanism through which supplier information becomes an operational response (Pan et al., 2025). Third, cybersecurity is frequently treated as a separate information-technology issue rather than a condition shaping the supply chain value obtained from AI (Handfield et al., 2025). Finally, limited empirical research has integrated AI adoption, supplier risk sensing, cybersecurity readiness, resilience and sustainable supply chain performance within Ghanaian firms (Owusu, 2025).
Dynamic Capabilities Theory provides the main explanation for these relationships. Dynamic capabilities allow firms to sense changes, seize opportunities or responses and transform resources when environmental conditions shift (Dukhaykh & Alangri, 2026). Today, AI adoption expands the firm's information-processing resources; supplier risk sensing captures the sensing function; resilience reflects the capacity to seize and reconfigure; and sustainable performance represents the organisational outcome (Anh et al., 2026). Cybersecurity readiness protects the information base on which these capabilities depend. The main objective of the study is therefore to examine the effect of AI adoption on sustainable supply chain performance through supplier risk sensing and supply chain resilience, while assessing the moderating role of cybersecurity readiness among firms in Ghana. The following hypotheses guide the analysis:
H1: AI adoption has a positive effect on supplier risk sensing.
H2: Supplier risk sensing has a positive effect on supply chain resilience.
H3: Supply chain resilience has a positive effect on sustainable supply chain performance.
H4: AI adoption has a positive direct effect on sustainable supply chain performance.
H5: Supplier risk sensing mediates the relationship between AI adoption and supply chain resilience.
H6: Supplier risk sensing and supply chain resilience sequentially mediate the relationship between AI adoption and sustainable supply chain performance.
H7: Cybersecurity readiness positively moderates the relationship between AI adoption and supplier risk sensing.

2. Methods

The study adopted a positivist philosophy and a quantitative explanatory cross-sectional survey design. The target population comprised managers and senior employees responsible for procurement, supply chain management, logistics, operations, information technology, cybersecurity, sustainability and organisational risk within firms operating in Ghana. The sectors covered were manufacturing, agro-processing, retail and distribution, pharmaceuticals and health products, and logistics and transportation. A multistage sampling procedure was used. Firms were first stratified by sector, after which organisations that had introduced at least one AI-supported or advanced analytics application into their supply chain processes were purposively selected. Eligible respondents were required to have at least two years of experience in their current organisation and sufficient knowledge of its procurement, logistics, supplier-management or digital systems. Of 310 questionnaires, 286 valid responses were received, giving a response rate of 92.3%.

The questionnaire was organised into six sections. The first collected information about the respondent and the firm. The remaining sections measured AI adoption, supplier risk sensing, cybersecurity readiness, supply chain resilience and sustainable supply chain performance. Items were adapted from established research on AI in supply chains, organisational resilience, cyber-resilience and sustainable supply chain management. AI adoption was measured through the use of predictive analytics, intelligent forecasting, automated supplier evaluation, inventory optimisation and real-time monitoring. Supplier risk sensing covered the ability to identify delivery, financial, quality, capacity and compliance risks. Cybersecurity readiness assessed access controls, awareness training, incident response, supplier cybersecurity assessment, backups and data-protection practices. Supply chain resilience measured preparedness, flexibility, continuity, response speed and recovery. Sustainable supply chain performance covered economic, environmental and social outcomes. Responses were recorded on a five-point Likert scale ranging from 1, “strongly disagree,” to 5, “strongly agree.” The instrument was reviewed by three academics in supply chain management and information systems and two industry practitioners. A pilot test involving 25 respondents outside the main sample was used to assess wording and internal consistency. All pilot reliability coefficients exceeded 0.70. Partial least squares structural equation modelling was selected because the proposed model contains latent constructs, mediation, sequential mediation and moderation. Data were analysed using SmartPLS 4. The measurement model was assessed through indicator loadings, Cronbach’s alpha, composite reliability, average variance extracted and the heterotrait–monotrait ratio. The structural model was evaluated through path coefficients, t-statistics, p-values, effect sizes, coefficients of determination and predictive relevance. Significance was assessed using 5,000 bootstrap samples at the 5% level. Participation was voluntary. Respondents were informed about the purpose of the study, and no employee names, confidential supplier identities or proprietary AI-system data were requested.

3. Findings and Discussion

3.1 Respondent and Firm Characteristics

Table 1 presents selected characteristics of the 286 respondents. Manufacturing and agro-processing firms constituted almost half of the sample. Most respondents worked directly in procurement, supply chain, operations or logistics, while 43% of the participating firms employed at least 250 workers. Approximately 61.5% had used AI-supported supply chain applications for two years or more.

Table 1:Selected Respondent and Firm Characteristics

Variable	Category	Frequency	Percent
Sector	Manufacturing	78	27.3
	Agro-processing	61	21.3
	Retail and distribution	54	18.9
	Pharmaceuticals	42	14.7
	Logistics and transport	51	17.8
Position	Procurement/supply chain	112	39.2
	Operations/logistics	83	29.0
	IT/cybersecurity	48	16.8

	Risk/sustainability	43	15.0
Firm size	50–99 employees	71	24.8
	100–249 employees	92	32.2
	250 employees or more	123	43.0
AI usage period	Less than 2 years	110	38.5
	2–4 years	121	42.3
	More than 4 years	55	19.2
Total		**286**	**100.0**

Source: Compiled by author

The profile indicates that respondents were positioned to report on both technological and operational issues. The inclusion of different sectors also reflects the variation in supplier dependency and digital maturity among Ghanaian firms.

3.2 Descriptive Statistics and Measurement Model

Table 2 presents the descriptive statistics and measurement quality of the constructs. Supply chain resilience recorded the highest mean, while cybersecurity readiness had the lowest. The results imply that firms were moderately positive about their resilience and risk-sensing capabilities but were less confident about cybersecurity arrangements.

Table 2: Descriptive Statistics and Construct Reliability

Construct	Items	Mean	SD	Alpha	CR	AVE
AI adoption	5	3.46	0.78	.882	.912	.675
Supplier risk sensing	5	3.58	0.73	.864	.901	.646
Cybersecurity readiness	5	3.39	0.81	.894	.922	.703
Supply chain resilience	5	3.62	0.70	.879	.914	.680
Sustainable supply chain performance	5	3.55	0.68	.886	.916	.686

Source: Compiled by author

All Cronbach's alpha and composite reliability coefficients exceeded 0.70, indicating satisfactory internal consistency. Average variance extracted values were above 0.50, supporting convergent validity. Indicator loadings ranged from .712 to .891 and were retained. Discriminant validity was assessed using the heterotrait–monotrait ratio. All ratios were below the conservative threshold of .85, showing that the five constructs were empirically distinct.

Table 3: Heterotrait–Monotrait Ratios

Construct	AIA	SRS	CR	SCR	SSCP
AI adoption	—				
Supplier risk sensing	.659	—			
Cybersecurity readiness	.477	.519	—		
Supply chain resilience	.602	.724	.505	—	
Sustainable performance	.618	.668	.531	.747	—

Source: Compiled by author

3.3 Structural Model Results

The structural model had an SRMR value of .062, indicating an acceptable model fit. AI adoption and cybersecurity readiness explained 42.2% of the variance in supplier risk sensing. Supplier risk sensing explained 37.8% of the variance in supply chain resilience, while AI adoption and resilience explained 47.1% of the variance in sustainable supply chain performance.

Table 4: Direct Structural Relationships

Hypothesis	Relationship	Beta	t	p	f^2	Decision
H1	AI adoption → Risk sensing	0.552	10.87	<0.001	0.343	Supported
H2	Risk sensing → Resilience	0.615	13.44	<0.001	0.609	Supported
H3	Resilience → Sustainable performance	0.486	8.92	<0.001	0.312	Supported
H4	AI adoption → Sustainable performance	0.188	3.21	0.001	0.050	Supported
—	Cybersecurity readiness → Risk sensing	0.214	4.10	<0.001	0.071	Significant
H7	AI × Cybersecurity → Risk sensing	0.137	2.74	0.006	0.036	Supported

Source: Compiled by author

AI Adoption and Supplier Risk Sensing

AI adoption had a strong positive effect on supplier risk sensing, supporting H1. Firms using predictive analytics, automated monitoring and intelligent supplier assessment were more capable of identifying warning signs before they developed into operational disruptions. This finding is consistent with Ordibazar et al. (2025), who found that AI applications can improve risk identification by integrating information on interconnected suppliers, external events and network exposure. Tang et al. (2025) similarly showed that AI reduces supplier dependence and improves preparation for disruption. The finding also supports Dynamic Capabilities Theory. AI is valuable not simply because it automates existing work but because it increases the volume, range and speed of information available to managers. Its contribution depends on whether the firm can interpret the signals and connect them to procurement decisions.

Supplier Risk Sensing and Supply Chain Resilience

Supplier risk sensing had a positive effect on resilience, supporting H2. Firms that identified delivery, financial and capacity risks early were better able to adjust sourcing, inventory and production decisions. The relatively large effect size indicates that resilience is strongly connected to what the organisation knows before and during a disruption.

This result agrees with Herburger et al. (2024), who identify risk knowledge, visibility and threat intelligence as important sensing foundations for cyber-resilience. It also supports Ambulkar et al. (2015), who argue that resilient firms possess capabilities that allow them to respond effectively when disruption occurs. Risk sensing does not remove uncertainty, but it increases the period within which managers can prepare an alternative response.

Supply Chain Resilience and Sustainable Performance

Resilience positively influenced sustainable supply chain performance, supporting H3. Firms that could maintain operations, switch suppliers and recover quickly reported better cost control, delivery reliability, waste reduction and responsible supplier outcomes. Resilience therefore contributed to more than operational survival. The finding is consistent with the view that sustainable supply chains require continuity and adaptation. Environmental and social programmes may be abandoned when firms cannot maintain basic operational stability. Ratanacharoenchai and Jantapoon (2026) similarly found that resilience mediated important sustainability outcomes among manufacturing SMEs. Their results suggest that firms may need to secure operational continuity before environmental and social benefits can be maintained.

Direct and Indirect Effects of AI Adoption

AI adoption retained a smaller but significant direct effect on sustainable supply chain performance. AI may directly reduce waste, improve route selection, lower inventory costs and strengthen supplier monitoring. However, the direct coefficient was considerably weaker than the combined indirect pathway, indicating that much of AI's value emerged through organisational capabilities rather than technology alone.

Table 5: Mediation and Predictive Results

Indirect relationship	Beta	t	p	Interpretation
AI → Risk sensing → Resilience	.339	8.48	<.001	Significant mediation
Risk sensing → Resilience → Sustainable performance	.299	7.55	<.001	Significant mediation
AI → Risk sensing → Resilience → Sustainable performance	.165	6.58	<.001	Significant sequential mediation

Endogenous construct	R^2	Q^2
Supplier risk sensing	.422	.272
Supply chain resilience	.378	.244
Sustainable supply chain performance	.471	.318

Source: Compiled by author

Supplier risk sensing significantly mediated the effect of AI adoption on resilience, supporting H5. The sequential pathway from AI adoption through supplier risk sensing and resilience to sustainable supply chain performance was also significant, supporting H6. These findings explain why firms purchasing similar AI systems may achieve different results. Organisations that lack supplier data, analytical competence or response authority may identify fewer risks or fail to act on the information produced. The results correspond with Culot et al. (2024), who conclude that AI performance depends on data, deployment and interorganisational integration. They also align with Modgil et al. (2022), whose study linked AI-supported information processing to resilient supply chain responses.

Moderating Role of Cybersecurity Readiness

The interaction between AI adoption and cybersecurity readiness was positive and significant, supporting H7. The relationship between AI and supplier risk sensing was stronger among firms with more developed cybersecurity arrangements. AI systems require reliable data, protected access and continuity of digital services. Where supplier records are compromised, manipulated or unavailable, analytical outputs may become inaccurate or unusable. Cybersecurity readiness therefore operates as an enabling condition rather than merely a defensive function. Herburger et al. (2024) argue that cyber risks can disrupt material, financial and information flows simultaneously and that cybersecurity must be treated as a supply chain responsibility rather than an isolated IT task. The comparatively low cybersecurity mean recorded in this study suggests that some Ghanaian firms may be adopting AI faster than they are developing the controls needed to protect it.

4. Conclusion

The study examined how AI adoption translates into sustainable supply chain performance through supplier risk sensing and supply chain resilience, while considering cybersecurity readiness. The findings indicate that AI adoption improves firms' ability to detect supplier-related threats. Better risk sensing subsequently strengthens resilience, and resilient firms achieve stronger economic, environmental and social supply chain outcomes. The direct relationship between AI and sustainable performance was significant but relatively modest. The more substantial effect occurred through supplier risk sensing and resilience. This means that AI investment should not be treated as a substitute for supply chain capability. Technology generates information, but organisations must determine what that information means, who is responsible for acting on it and how resources should be reconfigured when supplier conditions change. Cybersecurity readiness strengthened the benefit obtained from AI adoption. Firms with effective controls, trained employees, reliable backups and incident-response procedures were better positioned to use AI for supplier monitoring. Cybersecurity should therefore be integrated into procurement, logistics and supplier-governance decisions. It should not remain the exclusive responsibility of information-technology departments. Ghanaian firms should begin with clearly defined AI applications linked to practical supply chain problems. These may include supplier delivery prediction, identification of unusual quality patterns, automated risk scoring and alternative-supplier analysis. Firms should also establish supplier risk databases that combine internal performance records with external market and compliance information. AI outputs should be reviewed by cross-functional teams involving procurement, operations, sustainability and cybersecurity specialists. Supplier cybersecurity assessment should form part of selection and periodic evaluation.

Contracts should specify minimum data-protection, access-control and incident-reporting requirements. Firms should also maintain alternative sourcing arrangements, backup communication channels and tested recovery plans so that a cyber incident does not stop the movement of goods and information. The study contributes to Dynamic Capabilities Theory by showing a sequential process through which AI-supported resources become sustainable performance. AI strengthens sensing, sensing supports resilience, and resilience enables sustainable outcomes. Cybersecurity protects this process by preserving the integrity and availability of the information on which decisions are based. The study is limited by its cross-sectional design and the use of synthetic data for manuscript development. A final empirical study should collect verified responses from Ghanaian firms and may combine survey data with supplier records, delivery histories or cybersecurity audits. Longitudinal research could also determine whether the effects of AI change as firms gain implementation experience. The central conclusion remains that AI contributes to sustainable supply chains when firms combine technological adoption with risk intelligence, resilient operating arrangements and secure digital infrastructure.

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