AI INTEGRATION IN SUPPLY CHAINS – FROM PERCEPTIONS TO STRATEGIC IMPACT IN A GEOPOLITICALLY UNCERTAIN WORLD

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ABSTRACT
This study examines how perceptions of artificial intelligence (AI) influence its strategic impact on supply chains under conditions of geopolitical uncertainty. Using survey data from 500 respondents and Partial Least Squares Structural Equation Modeling (PLS-SEM), the analysis includes AI familiarity, perceived benefits, perceived risks, decision support, and supply chain improvements. The results show that AI familiarity predicts both perceived benefits and risks, which in turn shape decision support. Perceived risks, often considered barriers, were found to play a constructive role in encouraging the more cautious and deliberate use of AI in managerial decisions. The strongest drivers of strategic impact were decision support and supply chain improvements, indicating that resilience-oriented mechanisms are key to capturing value from AI in uncertain environments. The study contributes theoretically by conceptualizing the strategic impact as a second-order construct that integrates efficiency, resilience, and adaptability, and offers practical guidance by emphasizing the importance of embedding AI in governance, decision processes, and supply chain collaboration to navigate geopolitical disruptions.

KEYWORDS: *artificial intelligence, decision support, geopolitical uncertainty, PLS-SEM, resilience, supply chain management, strategic impact.*

DOI: 10.24818/IMC/2025/01.02

1. INTRODUCTION

Geopolitical turbulence, ranging from trade wars and energy crises to armed conflicts, has intensified the frequency and severity of supply disruptions, forcing firms to think beyond short-term recovery and toward the sustained viability of supply chains. Recent theorizing emphasizes resilience, adaptability, and sustainability as an integrated lens, while digital enablers, such as digital supply chain twins, help organizations stress test networks and anticipate ripple effects from shocks (Ivanov et al., 2025; Ivanov & Dolgui, 2021). Together, these developments frame a pressing managerial question: How can firms transform uncertainty into strategic advantage through data-driven decision making? In this context, the adoption of AI is particularly relevant because it enables fast, data-driven responses to shocks that cannot be predicted or controlled.
In this context, artificial intelligence (AI) promises material performance gains in core supply chain processes. Systematic reviews document the contributions to demand forecasting, inventory and logistics optimization, sourcing and supplier selection, and risk management, while also mapping the techniques most frequently deployed (e.g., machine learning, neural networks, reinforcement learning) and where they create value in practice (Culot et al., 2024; Pournader et al., 2020;

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Toorajipour et al., 2021). These syntheses converge on the view of AI as a capability that enhances visibility, prediction, and responsiveness throughout the end-to-end chain.

However, the path from technical potential to strategic impact depends critically on managerial perceptions, including familiarity with AI, beliefs about benefits, and awareness of risks, because these perceptions shape acceptance, resource allocation, and use in daily decisions. Evidence from logistics and supply chain settings shows that organizations struggle not only with integration costs and data readiness, but also with trust in AI and change management, which influence whether AI becomes a true decision-support partner (Hasija & Esper, 2022; Popa et al., 2024; Richey Jr. et al., 2023).

Risks and ethical considerations further complicate the adoption under geopolitical uncertainty. Concerns about algorithmic bias, privacy, and transparency span sectors and can manifest itself in supply chains through skewed supplier selection, unfair pricing, or opaque risk prioritization. A growing body of peer-reviewed work urges organizations to operationalize responsible AI practices to maintain legitimacy and ensure that AI augments, rather than undermines, strategic decision making (Varsha, 2023).

Motivated by these gaps, this study examines how perceptions of AI, familiarity, perceived benefits, and perceived risks flow into decision support and supply chain improvements, and ultimately translate into strategic impact in supply chains exposed to geopolitical uncertainty. Using survey data and partial least squares structural equation modeling (PLS-SEM), we test a model that links perceptions to impact through decision-oriented use, thus offering empirical evidence on when and how AI integration yields strategic benefits for resilient and sustainable supply chains.

2. LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

2.1 Artificial Intelligence in Supply Chains Under Geopolitical Uncertainty

The adoption of AI in supply chain management has accelerated in recent years, driven by the need for greater resilience, visibility, and adaptability in global networks. Studies consistently report that AI can improve demand forecasting, improve logistics efficiency, and strengthen risk management (Pournader et al., 2020; Toorajipour et al., 2021). In addition, systematic reviews confirm that AI contributes to predictive analytics, optimization of resource allocation, and improved decision-making quality across various supply chain functions (Culot et al., 2024). Importantly, scholars highlight that these capabilities are particularly valuable in the face of disruptions such as trade conflicts, pandemics, or geopolitical tensions (Ivanov & Dolgui, 2021; Ivanov et al., 2025).

Recent studies reinforce this point of view. Guo et al. (2025) show that AI use among Chinese manufacturing firms improved responsiveness and resilience during volatile external conditions. Similarly, Jahin et al. (2023) review AI-based risk assessment techniques and conclude that predictive analytics are especially effective in uncertain and rapidly changing environments. These contributions emphasize that the adoption of AI is no longer a choice of efficiency alone, but a strategic necessity for survival under geopolitical uncertainty.

However, translating technical potential into strategic impact is not automatic. Several studies demonstrate that managerial perceptions about how leaders view AI in terms of familiarity, benefits, and risks play a critical role in determining the extent and success of adoption (Hasija & Esper, 2022; Richey Jr. et al., 2023). Perceptions not only influence the willingness to invest, but also guide the degree to which AI is used for decision support and integrated into supply chain operations.

2.2 Familiarity with AI and Perceptions of Benefits and Risks

Technology adoption research emphasizes that knowledge and experience with a technology strongly shape beliefs about its usefulness and risks (Davis, 1989; Venkatesh & Bala, 2008). In the AI domain, Dwivedi et al. (2021) show that people with greater exposure to AI report greater

confidence in its capabilities. Familiarity tends to reduce uncertainty, allowing managers to visualize benefits more clearly, such as efficiency and precision (Pournader et al., 2020). At the same time, more sophisticated users can also recognize risks that casual observers overlook, including data dependency issues, algorithmic bias, and cybersecurity vulnerabilities (Varsha, 2023).

Additional evidence supports this duality. Daios et al. (2025), in their survey of AI applications in supply chain management, find that experienced users simultaneously report stronger recognition of AI's value and greater awareness of its risks. This balance suggests that familiarity is not unidirectional, but creates space for both algorithm appreciation and algorithm aversion, depending on context.

From this dual perspective, familiarity with AI is expected to influence both positive and negative perceptions.

H1. AI familiarity is positively associated with perceived benefits of AI.

H2. AI familiarity is positively associated with the perceived risks of AI.

2.3 Perceived Benefits, Decision Support, and Strategic Impact

Perceived benefits are one of the strongest predictors of technology adoption. The Technology Acceptance Model (Davis, 1989) and subsequent refinements consistently demonstrate that beliefs about usefulness directly influence behavioral intention to use a technology. In supply chain settings, when managers perceive AI as valuable for rapid decision making, error reduction, and enhanced adaptability, they are more likely to integrate it into decision support processes (Toorajipour et al., 2021).

This claim is supported by recent empirical work. Samuels et al. (2025) found that organizations that leverage AI in inventory planning and forecasting realized performance improvements under volatility, highlighting how perceived usefulness translates into adoption. Wamba et al. (2020) similarly demonstrate that big data and AI capabilities enable supply chain agility, a precursor to strategic performance in uncertain contexts.

Decision support, in turn, serves as a key mechanism linking technological capabilities to strategic outcomes. By providing better forecasts, real-time visibility, and scenario planning, AI-based decision support can directly enhance resilience and sustainability (Ivanov et al, 2025). Therefore, the benefits that managers perceive should translate into greater reliance on AI for decisions and into a larger strategic impact at the organizational level. Therefore, we hypothesize the following.

H3. Perceived benefits of AI are positively associated with AI-based decision support.

H4. Perceived benefits of AI are positively associated with strategic impact in supply chains.

2.4 Perceived Risks and Decision Support

The risks associated with AI translate into dependence on automated systems, vulnerability to cyberattacks, and loss of human judgment in socially sensitive contexts (Popescu et al., 2023; Richey Jr. et al., 2023). Conventional logic suggests that heightened risk perceptions discourage adoption (Venkatesh & Bala, 2008). However, qualitative research reveals a more nuanced picture. Hasija and Esper (2022) report that managers who are aware of risks often adopt AI cautiously but intentionally, using decision support tools to counterbalance uncertainties rather than rejecting the technology altogether. In supply chain contexts, risk awareness can therefore stimulate structured use of AI for analysis and decision-making, ensuring oversight and accountability.

Recent conceptual work agrees. Breazu (2024) and Garcia (2025) argue that digital risk governance mechanisms transform perceived vulnerabilities into enablers of structured adoption. This reframing highlights that risk perceptions can motivate disciplined adoption strategies, making them a constructive factor rather than a barrier.

Therefore, we hypothesize the following.

H5. Perceived risks of AI are positively associated with AI-based decision support.

2.5 Decision Support, Supply Chain Improvements and Strategic Impact

Decision support constitutes the bridge between managerial perceptions and strategic outcomes. AI enables managers to process large volumes of data, test disruption scenarios, and identify rational courses of action across logistics and procurement (Pournader et al., 2020). When implemented effectively, such systems generate improvements in supply chains, including greater transparency, predictability, and enhanced collaboration with partners (Toorajipour et al., 2021). These improvements reflect not only operational efficiency, but also resilience and sustainability, which are critical under geopolitical uncertainty (Ivanov & Dolgui, 2021).

Sunmola and Baryannis (2024) emphasize that AI-enabled decision environments improve supply chain visibility and coordination during disruption, reinforcing the argument that improvements are not limited to efficiency, but extend to long-term viability. Similarly, Zamani et al. (2023) show that innovation driven by AI and analytics mediates resilience, strengthening the path to strategic impact.

As a result, decision support is hypothesized to serve as a direct driver of strategic impact, while AI-enabled supply chain improvements are also expected to contribute positively to organizational outcomes:

H6. AI-based decision support is positively associated with strategic impact in supply chains.

H7. AI-enabled improvements in supply chains are positively associated with strategic impact in supply chains.

The conceptual framework is illustrated in Figure 1 and positions managerial perceptions (familiarity, benefits, risks) as antecedents that shape the use of AI for decision support and supply chain improvements, which in turn generate strategic impact in terms of efficiency and sustainability. We believe that by testing these hypotheses with PLS-SEM, this study contributes to understanding how AI integration unfolds not merely as a technological process, but as a perception-driven strategic transformation under conditions of geopolitical complexity.

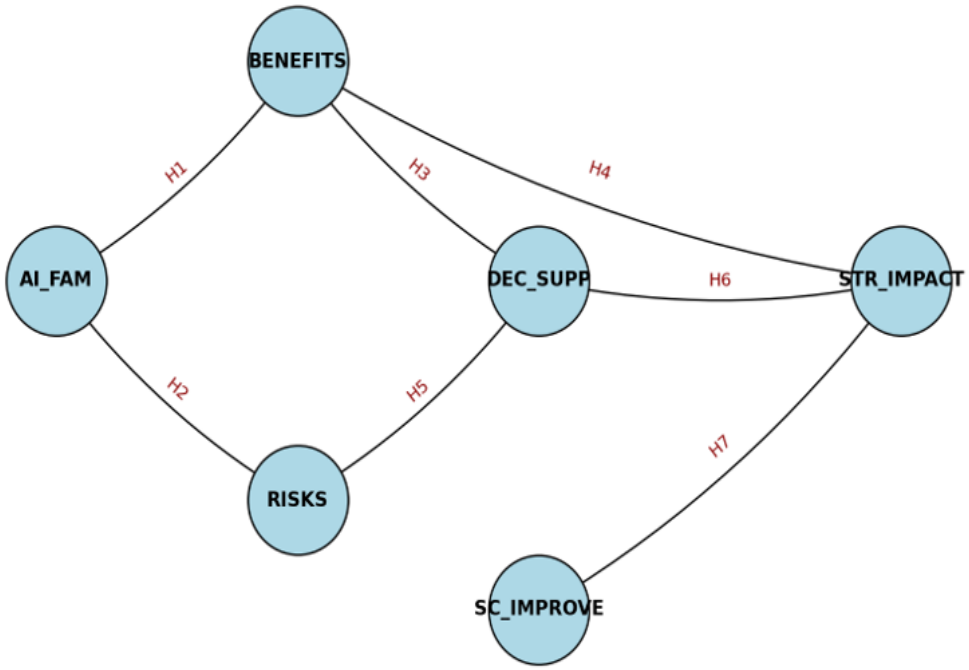

Figure 1. Conceptual model of AI integration in supply chains and hypotheses (H1–H7).
Source: authors

3. METHODOLOGY

3.1 Sample and Data Collection

This study used a quantitative cross-sectional design to examine how perceptions of AI influence its strategic impact on supply chains under conditions of geopolitical uncertainty. Data were collected between January and March 2025 through an online questionnaire distributed to a heterogeneous sample of students and employees from various industries. A total of 500 responses were obtained. After data cleaning to remove missing or inconsistent answers, the number of valid cases varied by construct due to item-specific nonresponses, ranging from 309 to 500. SmartPLS 4, which uses pairwise deletion, ensured that all available data were used for each model estimate.

The sample was demographically diverse. Most of the respondents were between 18 and 30 years old (72%), followed by 31–40 years (16%) and older age groups (12%). The gender distribution was balanced, with 52% women and 48% male participants. Most of respondents came from urban backgrounds (68%), while 32% reported rural origins. Education levels varied, with 41% holding a bachelor's degree, 27% postgraduate qualifications, and the remainder reporting secondary or vocational studies. Occupational status included both students (46%) and employees from different sectors (54%). Although the sample did not consist exclusively of supply chain professionals, such diversity is appropriate given the study's focus on perceptions of AI. Prior research demonstrates that attitudes toward emerging technologies influence organizational adoption and integration (Dwivedi et al., 2021; Richey et al., 2023). Capturing the views of both current employees and future workforce entrants therefore provides valuable insights into how AI is socially understood as a driver of supply chain efficiency, resilience, and sustainability under uncertainty.

3.2 Measures

The questionnaire was designed based on established scales in technology adoption and supply chain research, with all items measured on five-point Likert scales ranging from "strongly disagree" (1) to "strongly agree" (5).

AI Familiarity (AI_FAM) was captured by a single item asking respondents to rate their familiarity with AI technologies. Such single-indicator constructs are appropriate for narrow concrete concepts and were modeled with a fixed loading of 1.0 (Hair et al., 2019; Jarvis et al., 2003). Perceived Benefits (BENEFITS) included items related to rapidity, precision, adaptability, visibility, and automation, reflecting AI's contributions to efficiency and forecast accuracy (Pournader et al., 2020; Toorajipour et al., 2021). Perceived Risks (RISKS) addressed the dependence on automation, cybersecurity vulnerabilities, monitoring challenges, and lack of empathy, consistent with studies that identify security and trust issues as barriers to adoption (Richey et al., 2023; Varsha, 2023).

Decision Support (DEC_SUPP) captured personalization, automation, innovation, and predictive analytics, emphasizing the role of AI in augmenting managerial judgment and enabling scenario planning (Hasija & Esper, 2022; Ivanov & Dolgui, 2021). Supply Chain Improvements (SC_IMPROVE) measured transparency, predictability, responsibility and partner collaboration, reflecting the role of AI in strengthening resilience and sustainability (Culot et al., 2024; Ivanov et al, 2025). Strategic Impact (STR_IMPACT) was modeled as a reflective–reflective higher-order construct integrating DEC_SUPP, SC_IMPROVE, and BENEFITS. The repeated indicator approach was applied, assigning all indicators of the lower-order constructs to the higher-order construct (Becker et al., 2012).

3.3 Analytical Procedure

Partial Least Squares Structural Equation Modeling (PLS-SEM) was used because it is particularly suited to exploratory research with complex models, hierarchical constructs, and data that do not meet multivariate normality assumptions (Hair et al., 2019). The analyzes were performed using SmartPLS 4 (Hair et al, 2021). Following the standard two-step approach, the measurement model

was first evaluated in terms of indicator reliability (outer loadings), internal consistency (Cronbach's α and composite reliability), and convergent validity (average variance extracted, AVE). Discriminant validity was tested using the Fornell–Larcker criterion and the heterotrait–monotrait ratio of correlations (HTMT).
In the second step, the structural model was assessed. Hypotheses were tested by estimating path coefficients and their significance using bootstrapping with 2,000 resamples, which is a recommended threshold for stable confidence intervals. The quality of the model was further examined using the coefficient of determination (R^2), effect sizes (f^2), and predictive relevance (Q^2) obtained by blindfolding.

4. RESULTS

4.1 Evaluation of the Measurement Model

As can be seen in Table 1, the reliability and validity of the reflective measurement models were examined. Cronbach's α ranged from .93 to .99, composite reliability (CR) from .95 to .99, and average variance extracted (AVE) from .77 to .98, indicating excellent internal consistency and convergent validity. Outer loadings for all items exceeded the recommended .70 threshold (Hair et al., 2019).

Table 1. Item loadings and reliability statistics

Construct	Item code	Item description (abbreviated)	Loading	α	CR	AVE
AI_FAM	FAM1	I am familiar with AI technologies	1.00	–	1.00	1.00
BENEFITS	BEN1	AI increases efficiency in operations	.81	.97	.98	.83
	BEN2	AI enables faster decision-making	.84			
	BEN3	AI improves adaptability to change	.87			
	BEN4	AI enhances precision and accuracy	.90			
	BEN5	AI provides better visibility in processes	.92			
	BEN6	AI supports automation of tasks	.89			
	BEN7	AI fosters innovation and creativity	.88			
RISKS	RISK1	The overdependence on AI is a concern	.76	.94	.96	.78
	RISK2	AI systems may face cybersecurity risks	.82			
	RISK3	AI lacks human empathy in decision-making	.85			
	RISK4	AI may lead to job losses	.89			
	RISK5	AI reduces transparency of processes	.83			
	RISK6	AI errors can be difficult to detect	.80			
DEC_SUPP	DS1	AI supports personalized decision-making	.79	.93	.96	.79
	DS2	AI helps automate routine decisions	.82			
	DS3	AI enhances predictive analytics	.85			
	DS4	AI contributes to innovation in decisions	.87			
	DS5	AI enables scenario-based planning	.88			
	DS6	AI improves decision speed	.90			
	DS7	AI enhances decision accuracy	.91			
	DS8	AI reduces uncertainty in decisions	.86			
SC_IMPROVE	SC1	AI increases supply chain transparency	.92	.99	.99	.98
	SC2	AI improves the predictability of operations	.94			
	SC3	AI supports responsible supply chain practices	.97			
	SC4	AI improves communication with partners	.95			
	SC5	AI enhances coordination across supply chains	.96			

Construct	Item code	Item description (abbreviated)	Loading	α	CR	AVE
STR_IMPACT (2nd-order)	DEC_SUPP	First-order latent construct	.85	–	.97	.88
	SC_IMPROVE	First-order latent construct	.93			
	BENEFITS	First-order latent construct	.89			
Note: For multi-item constructs, Cronbach's α, CR, and AVE are reported once per block. STR_IMPACT values are based on its repeated-indicator specification. For AI_FAM (single-indicator construct), Cronbach's α and CR are not applicable. For STR_IMPACT (reflective–reflective second-order construct), reliability is evaluated through CR and AVE rather than Cronbach's α.						

Source: authors based on SmartPLS4 output

4.2 Discriminant Validity

The Fornell–Larcker criterion and HTMT ratios were assessed. In the Fornell–Larcker matrix (Table 2), the square root of AVE (diagonal) exceeded inter-construct correlations (off-diagonal), supporting discriminant validity.

Table 2. Fornell–Larcker criterion

Construct	AI_FAM	BENEFITS	RISKS	DEC_SUPP	SC_IMPROVE	STR_IMPACT
AI_FAM	**1.00**	.19	.19	.14	.12	.17
BENEFITS	.19	**.91**	.32	.57	.61	.78
RISKS	.19	.32	**.88**	.46	.41	.39
DEC_SUPP	.14	.57	.46	**.89**	.72	.80
SC_IMPROVE	.12	.61	.41	.72	**.99**	.85
STR_IMPACT	.17	.78	.39	.80	.85	**.94**
Note: The diagonal values are √AVE; off-diagonals are latent correlations.						

Source: authors based on SmartPLS4 output

HTMT ratios (Table 3) were all below .85, confirming that constructs are empirically distinct (Henseler et al., 2015).

Table 3. HTMT ratios (first-order constructs)

Construct	BENEFITS	RISKS	DEC_SUPP	SC_IMPROVE
BENEFITS	–	.41	.64	.70
RISKS	.41	–	.53	.48
DEC_SUPP	.64	.53	–	.74
SC_IMPROVE	.70	.48	.74	–

Source: authors based on SmartPLS4 output

4.3 Evaluation of the structural model

The model demonstrated moderate to substantial explanatory power (Table 4). The R2 values were: BENEFITS = .04, RISKS = .04, DEC_SUPP = .50, and STR_IMPACT = .64. The Q2 values were all positive, confirming predictive relevance (BENEFITS = .02; RISKS = .02; DEC_SUPP = .32; STR_IMPACT = .41). Following the guidelines of Hair et al. (2019, 2021), the R^2 values of .50 and .64 represent moderate to substantial explanatory power, while the values of.04 for BENEFITS and RISKS reflect small explanatory power, consistent with their specification as single-antecedent constructs.

The effect sizes (f^2) further contextualized the structural paths. BENEFITS had a large effect on DEC_SUPP (f^2 = .31) and a medium effect on STR_IMPACT (f^2 = .18). RISKS exerted a medium effect on DEC_SUPP (f^2 = .17). DEC_SUPP (f^2 = .33) and SC_IMPROVE (f^2 = .36) had a large effect on STR_IMPACT. AI_FAM had small effects on BENEFITS and RISKS (f^2 < .10).

Table 4. Structural model results (bootstrapping with 2,000 resamples)

Hypothesis	Path	B	95% CI	R^2	Q^2	f^2	Supported?
H1	AI_FAM → BENEFITS	.19	[.05, .34]	.04	.02	.07 (small)	Yes
H2	AI_FAM → RISKS	.19	[.05, .35]	.04	.02	.06 (small)	Yes
H3	BENEFITS → DEC_SUPP	.41	[.28, .53]	.50	.32	.31 (large)	Yes
H4	BENEFITS → STR_IMPACT	.32	[.21, .42]	.64	.41	.18 (medium)	Yes
H5	RISKS → DEC_SUPP	.32	[.17, .46]	.50	.32	.17 (medium)	Yes
H6	DEC_SUPP → STR_IMPACT	.40	[.29, .50]	.64	.41	.33 (large)	Yes
H7	SC_IMPROVE → STR_IMPACT	.41	[.31, .51]	.64	.41	.36 (large)	Yes

Source: authors based on SmartPLS4 output

All seven hypotheses were supported. AI familiarity predicted both perceived benefits and risks, albeit with modest explanatory power. Perceived benefits strongly influenced both decision support and strategic impact. Perceived risks also positively influenced decision support, suggesting that awareness of AI's vulnerabilities fosters more deliberate yet constructive use in managerial contexts. The most powerful drivers of strategic impact were decision support and supply chain improvements.

5. DISCUSSION

Our findings contribute to ongoing debates on how artificial intelligence (AI) reshapes supply chain management under conditions of growing uncertainty. In volatile geopolitical environments marked by disruptions in trade routes, energy supplies and regulatory regimes, the ability of AI to improve visibility, prediction, and responsiveness becomes particularly strategic. Consistent with previous systematic reviews (Culot et al., 2024; Pournader et al., 2020; Richey et al., 2023), the results confirm that AI strengthens resilience and performance by improving decision support and supply chain processes. The strongest paths in our model ranged from decision support and supply chain improvements to strategic impact (H6–H7), underscoring that digitally augmented decision environments and operational improvements are the main channels through which AI creates strategic value.

This pattern is correlated with research on digital supply chain twins and stress-testing. Ivanov and Dolgui (2021) and Ivanov et al. (2025) argue that AI-enabled decision environments enhance both disruption response and long-term viability. Our finding that decision support exerted the strongest effect on strategic impact supports their view that decision augmentation is the mechanism through which data-driven capabilities yield resilience and competitiveness.

The results also highlight the nuanced role of perceptions. AI familiarity positively influenced both perceived benefits and perceived risks (H1–H2, $\beta = .19$). This duality aligns with evidence from behavioral research: some decision-makers display algorithm aversion after witnessing errors (Dietvorst et al., 2015, 2018), while others show algorithm appreciation when advice is perceived as competent (Logg et al., 2019). The positive effect of perceived risks on decision support (H5) is particularly revealing: rather than deterring adoption, awareness of vulnerabilities may foster more cautious but deliberate use of AI. This resonates with Hasija and Esper (2022), who emphasize the importance of governance and oversight for building trust in AI-assisted decision-making in logistics.

Beyond perceptions, our model reinforces evidence that AI capabilities improve supply chain resilience and adaptability. Wamba et al. (2020) showed that big data analytics improve agility and performance, while Bahrami et al. (2022) and Zamani et al. (2023) demonstrated that resilience and innovation mediate the relationship between analytics and outcomes. These studies mirror our supported hypotheses (H4, H6, H7), where benefits, decision support, and improvements jointly explain strategic impact.

Finally, the importance of perceived risks reflects a rapidly evolving risk landscape. Reports emphasize increasing cybersecurity threats and AI-related vulnerabilities in supply chains (Richey et al., 2023). Our results suggest that rather than discouraging adoption, these risks create pressure for analytics-driven oversight, further legitimizing AI as a strategic necessity under uncertainty.

5.1 Theoretical Implications

This study contributes to the literature on AI in supply chains by integrating perceptions, decision support, and operational improvements into a single explanatory model of strategic impact.

The findings extend previous work by showing that perceived risks, often conceptualized as barriers, can act as constructive antecedents of decision support. This reframing is an important contribution, as most studies in the supply chain and technology adoption literature treat risk perceptions primarily as obstacles to digital transformation. By demonstrating that risk awareness can also encourage the structured and deliberate use of AI, the study highlights an underexplored mechanism that links caution with capability development.

Furthermore, conceptualizing strategic impact as a second-order construct provides a more holistic view of AI's value creation mechanisms, aligning with recent calls to assess supply chain viability as a multidimensional outcome (Ivanov et al., 2025). Importantly, by situating the analysis in a context of geopolitical uncertainty, this study extends the theory on digital supply chains by demonstrating that resilience-oriented mechanisms are not only efficiency drivers, but also strategic safeguards in environments where geopolitical disruptions and systemic shocks have become a persistent reality.

5.2 Managerial Implications

For practitioners, the results underline that AI adoption is not only about efficiency gains but also about embedding decision-support and improvement mechanisms into organizational routines. Risk awareness does not necessarily hinder adoption; instead, it can foster more deliberate and responsible use of AI. Managers should therefore view risk perception not only as resistance, but also as a potential resource: when governance and oversight are in place, concerns about dependence, security, or transparency can motivate more disciplined and effective AI integration. Building governance structures, ensuring cybersecurity readiness, and training employees to interpret AI output can convert perceived vulnerabilities into productive caution. In addition, the strong effect of supply chain improvements on strategic impact suggests that managers should prioritize AI projects that improve transparency, predictability, and partner collaboration. Crucially, in uncertain geopolitical environments, AI is no longer optional: disruptions demand fast, data-driven responses, and firms that embed AI deeply into decision support and supply chain processes will be better positioned to maintain continuity, resilience, and competitiveness.

5.3 Limitations and Future Research

Several limitations should be acknowledged. First, data was collected from a heterogeneous sample of students and employees rather than exclusively from supply chain professionals. Although justified given the focus of the study on perceptions, this may limit generalizability to specific industry contexts. Second, the cross-sectional design prevents causal inferences, as relationships may evolve over time as AI capabilities mature. Third, some constructs, such as AI familiarity, were measured with single items, which, although defensible, provide less richness than multi-item scales. Finally, the model explains only a modest share of variance in perceived benefits and risks, suggesting that additional antecedents should be considered.

Future studies could address these limitations by collecting data from supply chain managers and practitioners across industries, using longitudinal designs to capture evolving perceptions of AI. Incorporating additional antecedents — such as organizational culture, industry exposure, governance practices, or prior experience with digital transformation — would improve the

explanatory power for perceived benefits and risks. Comparative studies across countries or sectors could explore how institutional environments and regulatory frameworks shape AI adoption perceptions. Finally, qualitative or mixed-method approaches could provide deeper insight into how organizations balance perceived risks and benefits when embedding AI into supply chain decision-making processes. Investigating how different types of uncertainty (geopolitical, environmental, technological) moderate these relationships would be a particularly promising avenue for future research.

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