

## AI-Driven Risk Management and Energy Supply Chain Resilience: The Moderating Role of Supply Chain Complexity

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**Abstract.** This study examines the association between AI-driven risk management and energy supply chain resilience in Jordan, with supply chain complexity incorporated as a moderating variable. Grounded in dynamic capabilities theory, the study adopts a quantitative, cross-sectional design and draws on survey data collected from 248 supply chain, operations, risk management, and digital transformation professionals in Jordan's energy sector. Partial least squares structural equation modelling (PLS-SEM) was employed to test the hypothesized direct and moderating effects. The findings indicate a statistically significant positive association between AI-driven risk management and energy supply chain resilience, while supply chain complexity is found to significantly moderate this relationship, suggesting that the strength of the association varies across different levels of structural complexity within the supply chain. These results provide empirical evidence of a relationship between AI-driven capabilities and resilience outcomes in an emerging economy context and should be interpreted as associative rather than causal, given the cross-sectional research design. The study contributes to the logistics and informatics literature by offering sector-specific insights from Jordan's energy supply chain, where digital infrastructure and data-driven coordination mechanisms are still developing.

**Keywords:** AI-driven risk management, Energy supply chain resilience, Supply chain complexity, Information visibility, Logistics informatics, Emerging economies

## **1. Introduction**

The Jordanian energy sector is undergoing rapid transformation influenced by the volatility in the demand side, geopolitical turmoil, and the rapid shift to the renewable energy systems. In this regard, the resilience and continuity of energy supply are now strategic concerns. At the same time, technological developments in the field of artificial intelligence (AI) are reshaping the principles of risk management by introducing predictive analytics, real-time tracking, and autonomous decision-making in complex operational environments (Alhanatleh et al., 2024; Dey et al., 2024; Khaddam & Alzghoul, 2025). There is also an emerging body of research that indicates that AI-driven risk management systems can have a significant positive impact on the ability of supply chains to anticipate, absorb, and recover from disruption, especially in highly interdependent and uncertain sectors (Al-Khatib, 2025; Ojong, 2025). Simultaneously, an increasing amount of the literature suggests the applicability of AI-enabled capabilities in enhancing the results of operational resilience and sustainability in a wide range of sectors. The existing empirical research performed in the Jordanian setting and especially in the field of construction and retail business proves that AI-driven risk management systems have the potential of enhancing organizational flexibility, minimizing environmental risks, and facilitating the alignment with sustainable development objectives (Al Qudah et al., 2025; Al-Khatib, 2025). Although these perspectives offer a strong basis, their role in the energy supply chains is yet to be fully investigated. This loophole is especially acute in the context of the structural complexity and strategic significance of the energy systems, the effect of which may be cascading in economic and social terms. Additional studies on the renewable energy supply chains also place more importance on digital technologies such as AI, the Internet of Things (IoT), and blockchain to improve visibility, coordination, and responsiveness in multi-tier networks (Bag et al., 2025; Dey et al., 2024; Arunmozhi et al., 2022).

Beyond operational efficiency, the introduction of AI into energy systems is increasingly associated with broader logistics informatics and service science goals. From an informatics standpoint, AI enables real-time information processing, predictive data analytics, and intelligent coordination across distributed supply chain nodes, all of which are essential for maintaining service continuity in energy logistics networks (Al-Khatib, 2025). The governance of data flows, cybersecurity, and algorithmic transparency is particularly critical in this context. Recent research stresses that to realize the full resilience benefits of digital technologies in critical infrastructure sectors, trustworthy AI must be ensured through explainability, auditability, and resistance to cyber-attacks (Zebari and Musalhi, 2025; Ojong, 2025; Dey et al., 2024). One aspect that has not been critically analyzed in this discussion is the influence of supply chain complexity. Modern literature does not only define resilience as a functional attribute of technological capacity but also as an emergent phenomenon resulting from the interaction between organizational, technological, and network-based attributes. AI-driven risk management can either enhance resilience by improving information coordination or face diminishing returns due to higher uncertainty and system opacities in highly complex supply chains characterized by numerous stakeholders, interdependences, and dynamic information flows (Jum'a et al., 2024; Dey et al., 2024). This dual nature makes it important to study complexity as a boundary condition that predetermines the effectiveness of AI-based interventions in energy logistics systems.

These dynamics are especially strong within the context of Jordan. The strategic location of the country in the regional energy markets and the current work on the diversification of energy sources and digitalization of the infrastructure provide both opportunities and vulnerabilities (Ghaith et al., 2025). The operational environment is also complicated by changes in the global energy prices, geopolitical risks, and infrastructural constraints, which require more advanced and dynamic risk management strategies (Yewande et al., 2024; Sadaa et al., 2024). The energy supply chains in Jordan are also highly vulnerable, as the country is highly reliant on external energy sources including fuel imports, natural gas, and external power supply, thus making it more sensitive to political crisis in the region and international price fluctuations affecting energy supply. Historically, disruptions in the region's gas supplies, and volatility in global oil markets, have enhanced the costs of Jordanian

industries and added pressure to Jordan's energy logistics systems (Schuetze & Hussein, 2023). Furthermore, the need for conventional energy resources in Jordan is limited, resulting in dependence on cross-border energy supply chain networks that are subjected to transportation bottlenecks, border closures and geopolitical tensions in border countries (Ashour, Luckmann, & Fröhlich, 2025). Such structural conditions highlight the strategic value of resilient and data-driven risk management systems that can create more visibility, responsiveness and continuity in energy logistics networks in Jordan (Sandri, Hussein, & Alshyab, 2020). These obstacles notwithstanding, the policy orientation of Jordan towards the process of digital transformation and sustainable energy transition offers a promising platform on which to research how AI, risk management, and supply chain resilience interact.

From a logistics and informatics perspective, AI-driven risk management is not only a technological capability but also a mechanism for enhancing information visibility, real-time data flows, and coordinated decision-making across energy logistics networks (Twaissi et al., 2024). These dimensions are central to service continuity in energy systems, where disruptions in information processing can cascade into operational failures across interconnected supply nodes. Despite this relevance, prior studies have not adequately positioned AI-driven risk management within logistics and informatics frameworks, particularly in emerging economy energy contexts where digital infrastructure and information governance remain underdeveloped. Against this backdrop, a critical research gap exists in the current literature. While prior studies have examined AI capabilities and supply chain resilience in manufacturing and retail contexts (Belhadi et al., 2024; Dey et al., 2024), no empirical study has investigated the joint effect of AI-driven risk management and supply chain complexity on energy supply chain resilience in an emerging economy setting. Specifically, three gaps remain unaddressed. First, sector-specific empirical evidence from energy supply chains in developing countries is largely absent, despite the distinct structural characteristics of these systems, including high capital intensity, regulatory interdependence, and geopolitical exposure. Second, the moderating role of supply chain complexity in shaping the effectiveness of AI-based risk management has not been empirically tested within energy logistics networks. Third, the informatics dimension of AI adoption, namely its role in improving information flows, coordination, and service system responsiveness, has not been examined within the context of Jordanian energy supply chains.

This paper explores the connection between AI-based risk management and energy supply chain resilience, hypothesizing that the implementation of AI-based risk identification, prediction, and mitigation features will greatly improve the resilience of energy supply chains to disruptions and recovery. Moreover, the research investigates the moderating effect of supply chain complexity, where the degree of this relationship depends on the degree of complexity in the supply chain. In particular, the positive impact that AI-driven risk management has on resilience is supposed to be even greater with the increase in complexity since more complex supply chains need more complex data-driven risk management strategies to deliver on the potential of uncertainty and risk.

## **2. Literature Review and Hypotheses Development**

The theoretical foundation of this study rests on dynamic capabilities theory, which conceptualizes organizational resilience as a function of three core capabilities: sensing disruptions, seizing adaptive opportunities, and reconfiguring operational resources in response to environmental change (Naz et al., 2022; Wei'an and Yin, 2023; Singh et al., 2024). Within this framework, AI-driven risk management functions as an enabling infrastructure that strengthens each of these capabilities by providing real-time information processing, predictive analytics, and intelligent decision support across supply chain networks (Ali et al., 2024; Al-Ghalabi et al., 2024). This theoretical lens is particularly suited to energy supply chains, where tightly coupled networks spanning generation, transmission, and distribution amplify the impact of disruptions and demand rapid, synchronized responses. Industry 4.0 and Industry 5.0 perspectives serve as complementary supporting arguments, highlighting how technologies such as digital twins, predictive maintenance, and autonomous decision systems operationalize the sensing,

seizing, and reconfiguring capabilities described by dynamic capabilities theory (Zamani et al., 2022; Belhadi et al., 2024; Atadoga et al., 2024). Importantly, from a logistics and informatics standpoint, these capabilities are not merely operational tools but also mechanisms for enhancing information visibility, service coordination, and continuity across energy logistics networks.

A governance perspective complements the dynamic capabilities lens by emphasizing that AI-based risk management is only effective when supported by robust data governance, cybersecurity infrastructure, and algorithmic transparency. Trustworthy AI, expressed through explainability, auditability, and resilience to cyber-attacks, is a prerequisite for realizing resilience benefits in critical infrastructure sectors (Wei'an and Yin, 2023; Zebari and Musalhi, 2025; Khaddam and Alzghoul, 2025). This is especially relevant to energy systems in emerging economies like Jordan, where the risks that come with digitalization can undermine resilience if left unmanaged. Empirically, research on renewable energy supply chains demonstrates that AI-based big data analytics substantially improves resilience by enhancing information visibility, network coordination, and adaptive capacity among supply chain actors (Bag et al., 2025). Studies in operations and supply chain management consistently confirm that predictive analytics, real-time monitoring, and AI-driven decision-making improve disruption response and operational continuity, mechanisms directly applicable to the volatility, price variability, and climate-related risks characteristic of energy supply chains (Abu Lehyeh and Alzghoul, 2026; Naz et al., 2022; Belhadi et al., 2024).

Synthesizing these theoretical and empirical perspectives, dynamic capabilities theory provides a coherent explanation of how AI-driven risk management translates into resilience outcomes in energy supply chains. Specifically, AI strengthens the sensing capability by accelerating disruption detection and reducing the lag between risk emergence and managerial response. It strengthens the seizing capability through AI-driven decision support that enables rapid resource reallocation and scenario-based planning. Finally, it enhances reconfiguration by enabling real-time optimization of logistics operations, maintenance scheduling, and information flows across supply chain nodes (Baryannis et al., 2019; Naz et al., 2022; Bag et al., 2025). Although sector-specific empirical evidence from energy supply chains in emerging economies remains limited, the convergence of theoretical reasoning and cross-sector empirical findings supports a positive and significant relationship between AI-driven risk management and energy supply chain resilience. This relationship is likely conditioned by the degree of technological maturity, data governance quality, and organizational readiness for AI adoption. Accordingly, the following hypothesis is proposed:

H1: AI-driven risk management has a positive and significant effect on energy supply chain resilience.

It is based on the fact that technological capabilities are not in isolation but exist within structurally contingent environments, which are the basis of the proposition that supply chain complexity mediates the relationship between AI-driven risk management and energy SCR (Atieh Ali et al., 2023; Ghaith et al., 2026). The successfulness of AI-informed risk management within energy systems, which are multilayered networks with high asset specificity and interdependencies among the regulatory functions, is conditioned by the extent of supply chain complexity by default. Theoretically, it can be explained by the fact that dynamic capabilities theory suggests that the value of the sensing, seizing, and reconfiguring capabilities depends on the contextual factors, such as network structure, information processing requirements, and coordination intensity (Obeidat, 2026; Zhang and Xiao, 2023; Sreedharan et al., 2023). The current literature is consistent in its findings that AI proves to be a better way of improving SCR by enhancing visibility, predictive analytics, and fast decision-making within supply chain networks (Modgil et al., 2022; Liu et al., 2023; Tarawneh and Alzghoul, 2026; Xie et al., 2025). The capabilities give the organizations the ability to predict disruptive conditions, efficiently allocate resources, and redesign operations to respond to environmental uncertainty. Nevertheless, all such benefits are not equally large and consistent in all situations. The translation of AI capabilities into

resilience outcomes as a complex task in energy supply chains, where numerous actors are involved, cross-border flows, regulatory restrictions, and unstable market conditions exist, is becoming more reliant on the effectiveness with which such complexity is managed (Belhadi et al., 2024; Arora et al., 2024; Karot and Pornsing, 2024).

The empirical and conceptual studies propose that complexity has a two-fold and, occasionally, contradictory effect on the AI-SCR relationship. On the one hand, the greater the degree of complexity, the greater the worth of AI-based risk management due to the increase in the quantity, speed, and types of data that may be used to draw predictive conclusions and analyze the scenario (Ghaith, Albhirat, & Alzghoul, 2025). There, AI systems help to improve the ability to detect disruption, facilitate real-time monitoring, and coordinate the process of decision-making among distributed actors, which improves resilience capabilities (Liu et al., 2023; Xie et al., 2025; Singh et al., 2024). Conversely, too much complexity may add coordination frictions, information asymmetries, and implementation obstacles that limit the efficacy of AI-based interventions. The advantages of AI can be weakened in highly fragmented or low-integrity networks because of the constraints in the quality of data, its interoperability, and alignment to the organization (Iftikhar et al., 2024; Liu et al., 2023; Al-kasasbeh et al., 2022). Supply chain complexity in the energy setting specifically takes various facets as illustrated by the breadth of the network, process interdependencies, dispersion of information, and regulatory heterogeneity. All these dimensions have various interactions with risk management based on AI. As an example, the level of information complexity would contribute to the usefulness of the AI-based analytics, as it would allow one to understand the possible pathways of disruptions in a deeper way and, therefore, could strengthen the AI-SCR connection (Liu et al., 2023; Xie et al., 2025). Equally, the degree of process interdependence is higher, which makes the coordination mechanisms that make use of AI more significant since they can coordinate activities between the upstream and downstream operations and reconfigure the system in a short period of time (Karot and Pornsing, 2024). On the one hand, the regulatory and geopolitical complexity can both hinder and benefit AI performance based on the level of development of the governance systems and digital systems used to control and make decisions (Iftikhar et al., 2024; Liu et al., 2023).

Notably, the complementary organizational and technological capabilities of a firm also determine whether complexity is expected to strengthen or constrain the AI-SCR relationship. When adequate data governance frameworks, information systems standardization, and inter-organizational collaboration mechanisms are in place, higher complexity increases the value of AI-driven risk management by generating richer data environments, greater coordination demands, and more complex disruption scenarios that AI systems are well-suited to address (Belhadi et al., 2024; Liu et al., 2023; Iftikhar et al., 2024). Under these conditions, complexity acts as a positive amplifier: the greater the complexity, the more indispensable AI-driven risk management becomes for maintaining information visibility, coordinating logistics flows, and ensuring service continuity across distributed energy networks. Conversely, when enabling conditions are absent, extreme complexity may introduce data fragmentation, interoperability barriers, and coordination frictions that limit AI effectiveness (Xie et al., 2025; Singh et al., 2024). However, given that Jordan's energy sector is actively investing in digital infrastructure and AI adoption, and given the empirical context of this study which targets professionals with direct AI and supply chain experience, the net moderating effect of complexity is expected to be positive. This is consistent with dynamic capabilities theory, which predicts that sensing and reconfiguring capabilities become more valuable, not less, as the environmental complexity and information processing demands of the supply chain increase (Modgil et al., 2022; Zhang and Xiao, 2023). The following directional hypothesis is therefore proposed:

**H2: Supply chain complexity positively moderates the relationship between AI-driven risk management and energy supply chain resilience.**

### **3. Research Gaps**

Even though there is a vast amount of literature on the topic of artificial intelligence (AI), supply chain resilience and digital transformation in recent years, the empirical evidence in the Jordanian context is still limited, especially in relation to energy supply chains.

First, recent empirical studies in Jordan have started to highlight the significance of AI and digital technologies in strengthening supply chain resiliency in the manufacturing, SME and industrial sectors. For instance, research in Jordanian manufacturing companies reveals that AI-based tools and digital technologies enhance communication, operational efficiency, agility and resilience outcomes (Alkhatib & Momani 2023, Alshawabkeh et al. 2024, Twaissi et al. 2024). Likewise, the results from the Jordanian SMEs indicate that the use of AI positively affects the resilience of supply chains by enhancing decision-making and the ability to respond to risks (Twaissi et al., 2024). Although there is growing evidence in the local context, these studies are largely focused on manufacturing and SMEs rather than the energy supply chain sector, which has more complex structural, geopolitical, and infrastructural challenges.

Second, although AI and digital technologies have been shown to have a positive impact on resilience-related outcomes in Jordanian studies, the impact of structural conditions in supply chains has not been sufficiently examined. Specifically, the effect of supply chain complexity, as a moderating variable, has not been studied in Jordan to explain how it affects the effectiveness of AI-based risk management in achieving resilience outcomes. Current Jordanian studies focus mainly on the direct links between AI and resilience (Alkhatib & Momani, 2023; Twaissi et al., 2024), without examining how different levels of structural complexity may strengthen or constrain these relationships.

Third, the digital transformation and analytics dimension are still underdeveloped in the logistics chain in Jordan, despite their exploration in the Jordanian supply chain. Current research highlights aspects of efficiency and resilience of operations, with less focus on the capacity of AI to provide information visibility, coordination efficiency and data-driven governance in complex logistics networks in real time. This limitation is particularly important in critical industries such as energy, where disruptions can generate cascading effects across supply chain operations. There is yet no comprehensive integration of this informatics perspective in the Jordanian empirical literature in the field of resilience.

Last but not least, Jordan has been a growing focus in the field of supply chain research, but most of the empirical works have been conducted in manufacturing, food processing and SMEs industries, while only a few have been focused on the energy supply chain sector. The energy supply chain is a highly relevant, but under-explored context due to Jordan's dependence on energy imports, geopolitical risks, and infrastructure constraints. As a result, there is a lack of an integrated empirical framework in Jordan that simultaneously explores AI-based risk management, the complexity of the supply chain, and the resilience of the energy supply chain.

Thus, this study fills this gap by empirically studying the relationship between AI in risk management and energy supply chain resilience in the Jordanian energy sector, with the examination of the moderating effect of supply chain complexity. By doing this, it adds to the body of literature on supply chains in Jordan, taking the empirical results and applying them to a more complex and strategic sector.

### **4. Methodology**

In this study, the research design is a quantitative and cross-sectional survey, which aims at examining the relations among the variables under study in an empirical manner: AI-driven risk management, Supply chain complexity, and Resilience of the Energy supply chain in Jordan. The use of the quantitative methodology is an especially suitable method considering that this study is meant to test the hypotheses established by theory and to compare and contrast the structural relationships among the latent constructs. In the field of operations and supply chain management, survey approaches have been

used extensively to gather data on organizational perceptions, technological capabilities, and outcomes of resilience in complex industrial contexts (Hair et al., 2021; Sarstedt et al., 2021).

The participants included professionals with roles in Jordan's energy industry that are directly related to the constructs of this study, such as supply chain managers, operations managers, risk managers, and digital transformation managers. In order to have an adequate knowledge of the AI applications, supply chain processes and operational risk, which is also a criterion-based approach, a Purposive Sampling was used to gain insights from all the respondents. The data were gathered within three months using a structured, self-administered online questionnaire which was sent to professionals, industry associations, and organizational sources within the Jordanian energy industry. The participants were asked to answer the questions voluntarily and they were assured of being anonymous and kept confidential to reduce social desirability bias and ensure that respondents answered candidly. 271 questionnaires were sent out, and 248 of these were considered valid and complete for analysis 91.5%.

The number of samples is considered adequate for analyzing the data in this study using Partial Least Squares Structural Equation Modelling (PLS-SEM). PLS-SEM is well-suited for the applications of complex theoretical model, moderation effects, and moderate samples and has been largely applied to supply chain and operations management studies (Hair et al., 2021; Sarstedt et al., 2021). The choice of perceptual and subjective measurement scales, in addition, is methodologically relevant to this study as the focal constructs, namely AI-driven risk management capability, supply chain complexity, and organizational resilience, are organizational constructs that are latent and hard to measure by objective indicators from the archival data. Subjective managerial assessments have been used as proxy measures for organizational capabilities in resilience and supply chain research, due to their connection to organizational operational experience, context awareness, and strategic assessments (Hair et al., 2021; Sarstedt et al., 2021). This is especially true in the emerging economy energy sectors like Jordan, where standardized public performance indicators at the level of AI adoption, disruption recovery from operations, and inter-organizational coordination are either not widely available or not easily accessible.

Furthermore, previous methodological studies show good convergence between perceptual and objective organizational measures, particularly when researchers have personal operational and managerial experience related to the measures they study. The respondents in this research work occupy professional positions that are directly linked to supply chain activities, risk management, and digital transformation, which therefore make their evaluations representative and reliable of the organizational practices and the ability to be resilient. In addition, subjective measures are particularly well suited for capturing the outcomes of dynamic capabilities and resilience, given that these constructs involve the capacity to adapt, the quality of the coordination, and the responsiveness to disruption, which are hard to measure with only objective measures (Wall et al., 2004). This makes the use of subjective multi-item scales in this study in line with the most widely used methodologies in supply chain, operations, and resilience studies.

The instrument was based on scales that were previously used and validated in the literature, and modified slightly to be relevant to the energy sector. Reflective, multi-item scales with a five-point Likert scale (1 = strongly disagree to 5 = strongly agree) were used to measure all constructs. Five items were adapted from Belhadi et al. (2024) and Singh et al. (2024) to operationalize AI-driven risk management (AIRM) and focused on the dimensions of predictive analytics capability, real-time monitoring, intelligent decision support, risk detection speed, and adaptive response capacity. Energy supply chain resilience (SCR) was assessed using six indicators adapted from Modgil et al. (2022) and Dey et al. (2024), covering anticipation, absorption, response, recovery, service continuity, and flexibility capabilities in the face of energy supply chain disruptions. It is important to note that supply chain resilience in this study was measured as a perceptual construct rather than an objective operational measure (e.g., actual disruption recovery time or logistics continuity records). This approach is widely adopted in supply chain resilience research due to the difficulty of obtaining standardized and comparable operational disruption data, particularly in emerging economy contexts. Five items were

adapted from Iftikhar et al. (2024) and Liu et al. (2023) to measure supply chain complexity (SSC), including supply chain breadth, process interdependence, supply chain information dispersion, regulatory complexity, and coordination complexity. A pre-test was also undertaken to test item clarity, content validity, and scale reliability, with a small sample of 22 energy sector experts and practitioners. Some minor wording changes were made, based on input from the pilots, prior to finalization of the instrument.

In a single-source, cross-sectional survey design, common method bias (CMB) is a possible concern, and two corrective procedures were used: one procedural and one statistical. In terms of its structure, the questionnaire clearly delineated independent, moderating, and dependent constructs in different sections, and ensured confidentiality to the respondents to minimize evaluation apprehension (Podsakoff et al., 2003). In terms of statistics, Harman's single-factor test was carried out by loading all the items into an EFA. This analysis showed that the highest single factor had an 31.4% of the variance, which is not enough for the 50% criterion, and indicated that the common method bias is not a critical concern in this data.

Table 1. Sample Characteristics (N = 248)

| Category                   | Frequency | Percentage (%) |
|----------------------------|-----------|----------------|
| <b>Job Role</b>            |           |                |
| Supply Chain Management    | 72        | 29.0           |
| Operations Management      | 68        | 27.4           |
| Risk Management            | 61        | 24.6           |
| Digital Transformation     | 47        | 19.0           |
| <b>Years of Experience</b> |           |                |
| Less than 5 years          | 44        | 17.7           |
| 5-10 years                 | 89        | 35.9           |
| 11-20 years                | 82        | 33.1           |
| More than 20 years         | 33        | 13.3           |
| <b>Education Level</b>     |           |                |
| Bachelor's Degree          | 103       | 41.5           |
| Master's Degree            | 112       | 45.2           |
| Doctorate (PhD)            | 33        | 13.3           |

## 5. Results

The results of the empirical research are provided in two steps of analysis. To determine the reliability and validity of the constructs, first, the measurement model is evaluated in order to make sure that the indicators are able to measure the concepts in a reliable and consistent way. This entails a review of internal consistency, convergent validity, and discriminant validity (Hair et al., 2021). The structural model is then tested to analyze the correlation between the study variables as well as test the hypotheses. The step entails the analysis of path coefficients, their statistical significance, and the strength of the relationships in the form of structural equation modeling. These analyses taken jointly give a clear picture of the soundness of the measurement instruments, as well as the validity of the hypothesized model. In the same way as in figure 1, the factor loadings used in the model show a high level of the reliability of the indicators in all constructs, which proves that the observed variables are sufficient to reflect their corresponding latent constructs. In the case of AIRM, all loadings of items are within the 0.825 to 0.858 range, which is above the recommended 0.70. This shows that the indicators will always represent the concept of AIRM with a high level of precision. In the same vein, the SCR construct has strong loadings ranging from 0.759 to 0.868 across six items. These values imply that every measurement item is important to the construct, and there are no signs of weak or low-performing

indicators. These loadings are consistent, and this supports the reliability and the unidimensionality of the SCR construct. In the case of SSC, the factor loading is 0.744 to 0.836 across five items, which is also above the acceptable value (Hair et al., 2021). Despite being slightly lower compared to those of AIRM and SCR, the values are within the reasonable range, signifying the satisfactory indicator reliability and that SSC is measured by its items sufficiently well.

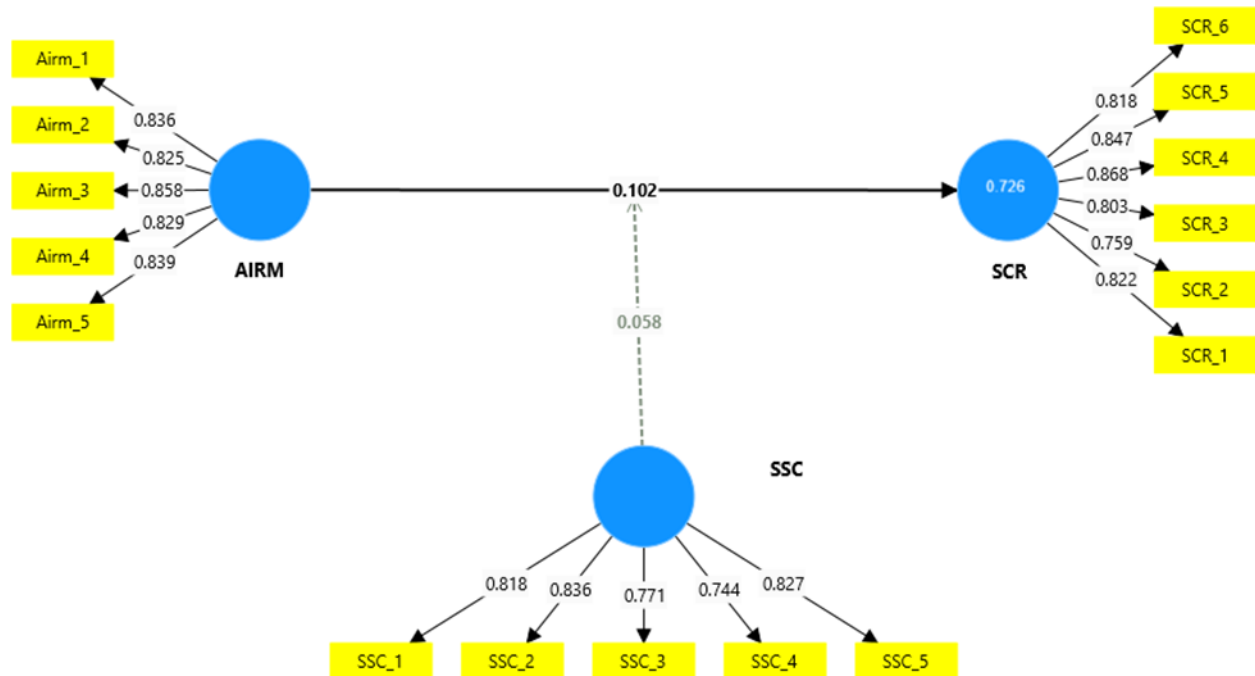


Fig.1: Measurement and Structural Model with Standardized Factor Loadings

The outcomes in Table 2 indicate that all constructs have great reliability and adequate convergent validity. The alpha of 0.859-0.902 is greater than the value of 0.70, which is the recommended level of alpha, indicating that the measurement items are highly internally consistent. SCR has the largest reliability (0.902), and then AIRM (0.894) and SSC (0.859) have the next highest reliability, thus demonstrating that all constructs are well measured in terms of consistency. Besides, composite reliability coefficients ( $\rho_a$  and  $\rho_c$ ) also confirm these results. The values of all the values are greater than the acceptable 0.70 (Sarstedt et al., 2017), and the 0.899 to 0.925 is the range of  $\rho_c$ . This means that the construct reliability is high, and it implies that the indicators provide a reliable measure of the latent variables represented by the indicators. The convergent validity is also determined since the average variance extracted (AVE) values show the establishment of convergent validity. All the AVE values are above the minimum of 0.50, with the values ranging from 0.640 to 0.730. This does mean that both constructs explain above 50 percent of the variance of the indicators (Hair et al., 2021; Fornell & Larcker, 1981), which proves that the items measure the intended constructs well.

Table 2. Reliability and Convergent Validity Assessment of Constructs

| Item                                                                                                                                                                                                        | Factor Loading | Cronbach's alpha | Composite Reliability ( $\rho_a$ ) | Composite Reliability ( $\rho_c$ ) | AVE          |
|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|----------------|------------------|------------------------------------|------------------------------------|--------------|
| <b>AI-Driven Risk Management (AIRM)</b>                                                                                                                                                                     |                | <b>0.894</b>     | <b>0.897</b>                       | <b>0.922</b>                       | <b>0.701</b> |
| <b>AIRM1:</b> Our organization leverages artificial intelligence-driven analytics to proactively identify and anticipate risks across energy supply chain networks through enhanced information visibility. | <b>0.836</b>   |                  |                                    |                                    |              |

|                                                                                                                                                                                 |              |              |              |              |              |
|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|--------------|--------------|--------------|--------------|--------------|
| <b>AIRM2:</b> AI-enabled systems facilitate real-time monitoring and integration of risk-related information across logistics and operational processes.                        | <b>0.825</b> |              |              |              |              |
| <b>AIRM3:</b> Artificial intelligence supports informed decision-making and effective coordination among supply chain partners during risk-related events.                      | <b>0.858</b> |              |              |              |              |
| <b>AIRM4:</b> AI applications improve the speed, accuracy, and reliability of detecting disruptions within energy supply chain and service operations.                          | <b>0.829</b> |              |              |              |              |
| <b>AIRM5:</b> Our organization utilizes AI capabilities to dynamically adapt and reconfigure supply chain processes in response to emerging risks and uncertainties.            | <b>0.839</b> |              |              |              |              |
| <b>Energy Supply Chain Resilience (SCR)</b>                                                                                                                                     |              | <b>0.902</b> | <b>0.906</b> | <b>0.925</b> | <b>0.640</b> |
| <b>SCR1:</b> The energy supply chain demonstrates a strong capability to anticipate potential disruptions through effective information sharing and risk visibility mechanisms. | <b>0.822</b> |              |              |              |              |
| <b>SCR2:</b> The supply chain is capable of absorbing disruptions while maintaining the stability of logistics and service operations.                                          | <b>0.759</b> |              |              |              |              |
| <b>SCR3:</b> The supply chain responds rapidly and effectively to disruptions through coordinated actions among network participants.                                           | <b>0.803</b> |              |              |              |              |
| <b>SCR4:</b> The supply chain can efficiently recover from disruptions by restoring critical logistics and operational functions.                                               | <b>0.868</b> |              |              |              |              |
| <b>SCR5:</b> The supply chain ensures continuity of energy service delivery despite the occurrence of operational disruptions.                                                  | <b>0.847</b> |              |              |              |              |
| <b>SCR6:</b> The supply chain exhibits a high degree of flexibility in adjusting its operations under conditions of uncertainty and environmental turbulence.                   | <b>0.818</b> |              |              |              |              |
| <b>Supply Chain Complexity (SSC)</b>                                                                                                                                            |              | <b>0.859</b> | <b>0.868</b> | <b>0.899</b> | <b>0.730</b> |
| <b>SSC1:</b> The energy supply chain is characterized by a broad and geographically dispersed network of stakeholders, increasing coordination demands.                         | <b>0.818</b> |              |              |              |              |
| <b>SSC2:</b> Supply chain processes exhibit a high level of interdependence, requiring continuous synchronization across multiple functional areas.                             | <b>0.836</b> |              |              |              |              |
| <b>SSC3:</b> Risk-related information is distributed across multiple digital platforms and systems, creating challenges for integration and transparency.                       | <b>0.771</b> |              |              |              |              |
| <b>SSC4:</b> The supply chain operates within diverse regulatory and institutional environments, complicating risk management and decision-making processes.                    | <b>0.744</b> |              |              |              |              |
| <b>SSC5:</b> Managing coordination and alignment among multiple supply chain actors represents a significant operational challenge.                                             | <b>0.827</b> |              |              |              |              |

The findings in Table 3 show the issue of discriminant validity according to the heterotrait-monotrait ratio (Henseler et al., 2015). The values of all the HTMTs are less than the recommended value of 0.85, which shows that the constructs are empirically differentiated from each other. In particular, the highest correlation of the constructs is the HTMT value between SCR and SSC (0.765), but still, it is close to the acceptable limit. On the same note, the values of AIRM vs SCR (0.758) and AIRM vs SSC (0.757) are also supportive of the fact that the two constructs are related but not overlapping. Besides that, the interaction construct (SSC x AIRM) presents relatively low HTMT values with AIRM (0.116), SCR (0.371), and SSC (0.346), which indicates that the moderating construct is distinct and it is not merged with the study variables (Henseler et al., 2015; Hair et al., 2021).

Table 3. Discriminant Validity Assessment Using HTMT Criterion

|                                  | <b>AIRM</b> | <b>SCR</b> | <b>SSC</b> |
|----------------------------------|-------------|------------|------------|
| <b>AI-Driven Risk Management</b> |             |            |            |
| <b>Supply Chain Resilience</b>   | 0.758       |            |            |
| <b>Supply Chain Complexity</b>   | 0.757       | 0.765      |            |
| <b>SSC x AIRM</b>                | 0.116       | 0.371      | 0.346      |

Table 4 shows the evaluation of the discriminant validity based on the Fornell-Larcker criterion. This approach determines the empirical distinctiveness of every construct in comparison with the rest by contrasting the square root of the average variance extracted (AVE) with inter-construct correlations. The diagonal items of the table (AIRM = 0.838, SCR = 0.820, SSC = 0.800) are the square root of the AVE of each of the constructs. As per the Fornell-Larcker criterion, such values ought to be higher than the inter-construct correlations of the same row and column. The findings reveal that in the case of AIRM, AVE (square root 0.838) has higher values than its correlation with SCR (0.686) and SSC (0.669). On the same note, SCR exhibits a square root of AVE (0.820) that is more than its correlations with AIRM (0.686) and SSC (0.651). In the case of SSC, AVE square root (0.800) is also bigger than their correlations with AIRM (0.669) and SCR (0.651). These results indicate that all constructs are in accordance with the Fornell-Larcker criterion, which indicates satisfactory discriminant validity (Fornell & Larcker, 1981; Hair et al., 2021). This means that all the constructs represent different facets of the model and are distinct enough with regard to one another, which lends credence to the validity of the overall measurement model.

Table 4. Discriminant Validity (Fornell–Larcker Criterion)

|                                  | <b>AIRM</b> | <b>SCR</b> | <b>SSC</b> |
|----------------------------------|-------------|------------|------------|
| <b>AI-Driven Risk Management</b> | 0.838       |            |            |
| <b>Supply Chain Resilience</b>   | 0.686       | 0.820      |            |
| <b>Supply Chain Complexity</b>   | 0.669       | 0.651      | 0.800      |

The hypothesis testing is shown in Table 5, which presents the direct and moderating effects within the structural model, along with the key model fit indicators. Before interpreting the path coefficients, the explanatory power of the structural model is assessed. The  $R^2$  value for energy supply chain resilience (SCR) is 0.312, indicating that the model explains approximately 31.2% of the variance in SCR, which is considered a moderate level of explanatory power and is acceptable for exploratory models in supply chain management research (Hair et al., 2021). The predictive relevance of the model was assessed using the  $Q^2$  statistic obtained through blindfolding. The  $Q^2$  value for SCR is 0.198, which is greater than zero, confirming that the model has satisfactory predictive relevance for this construct (Hair et al., 2021). Regarding effect sizes, the  $f^2$  value for the direct effect of AIRM on SCR is 0.089, which represents a small-to-moderate effect size according to Cohen's (1988) guidelines (small: 0.02; medium: 0.15; large: 0.35). The  $f^2$  value for the moderating effect of SSC x AIRM is 0.042, indicating a small but meaningful effect size as showed in table 6.

The results indicate a statistically significant positive relationship between AI-based risk

management (AIRM) and supply chain resilience (SCR) ( $\beta = 0.102$ ,  $t = 3.614$ ,  $p = 0.000$ ) statistically significantly and has a confidence interval [0.048, 0.157] that does not contain zero. However, this effect is quite small, implying that AIRM could not be considered a powerful independent driver of resilience. Instead, it is one among a number of facilitating mechanisms that lead to resilience results in the energy sector in a cumulative way. In this respect, the results suggest that the moderating role of the supply chain complexity offers more significant theoretical value as it elucidates the circumstances under which AIRM will be more or less effective. In line with this, the findings indicate that the effects of AIRM on resilience are contingent on the structure of the supply chain and are influenced by the contingency factors, which is why direct effects should not be considered solely. The direct effect of AIRM on SCR thus supports H1, with the caveat that practical significance requires consideration alongside statistical significance.

Furthermore, the moderating effect of SSC x AIRM on SCR is statistically significant ( $\beta = 0.058$ ,  $t = 3.165$ ,  $p = 0.002$ ). The confidence interval [0.022, 0.094] is entirely positive, indicating that supply chain complexity is associated with a change in the strength of the relationship between AIRM and SCR. That is, as supply chain complexity increases, the positive effect of AI-driven risk management on energy supply chain resilience appears to become stronger, supporting H2 as proposed. The existence of this significant interaction effect suggests that the AI-SCR relationship is not uniform but varies systematically with the degree of supply chain complexity, underscoring the importance of contextual factors in determining the value of AI-based interventions in energy logistics systems.

Table 5. Hypothesis Testing Results (Direct and Moderating Effects)

|                   | Original sample (O) | STDEV | T statistics | Confidence Interval |       | P values | Decision  |
|-------------------|---------------------|-------|--------------|---------------------|-------|----------|-----------|
|                   |                     |       |              | 2.5%                | 97.5% |          |           |
| AIRM -> SCR       | 0.102               | 0.028 | 3.614        | 0.048               | 0.157 | 0.000    | Supported |
| SSC x AIRM -> SCR | 0.058               | 0.018 | 3.165        | 0.022               | 0.094 | 0.002    | Supported |

Table 6. Structural Model Indicators ( $R^2$ ,  $Q^2$ , and Effect Sizes  $f^2$ )

| Path                                                                                                                                                                                           | $R^2$ | $Q^2$ | $f^2$ (AIRM) | $f^2$ (SSC×AIRM) |
|------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-------|-------|--------------|------------------|
| Supply Chain Resilience (SCR)                                                                                                                                                                  | 0.312 | 0.198 | 0.089        | 0.042            |
| Note: $R^2$ = coefficient of determination; $Q^2$ = predictive relevance (blindfolding); $f^2$ = effect size. Effect size benchmarks: small = 0.02, medium = 0.15, large = 0.35 (Cohen, 1988). |       |       |              |                  |

Figure 3 presents a simple slope plot depicting the relationship between AI-driven risk management (AIRM) and energy supply chain resilience (SCR) at low ( $-1$  SD), mean, and high ( $+1$  SD) levels of supply chain complexity (SSC). The plot reveals that the positive slope of AIRM on SCR becomes progressively steeper as SSC increases. At low levels of complexity, the effect of AIRM on SCR is positive but relatively modest (slope = 0.044). At mean levels of complexity, the relationship strengthens noticeably (slope = 0.102). At high levels of complexity, the AIRM–SCR slope is at its steepest (slope = 0.160), indicating that AI-driven risk management delivers its greatest resilience value precisely in the most complex supply chain environments. This pattern is consistent with H2 and with dynamic capabilities theory.

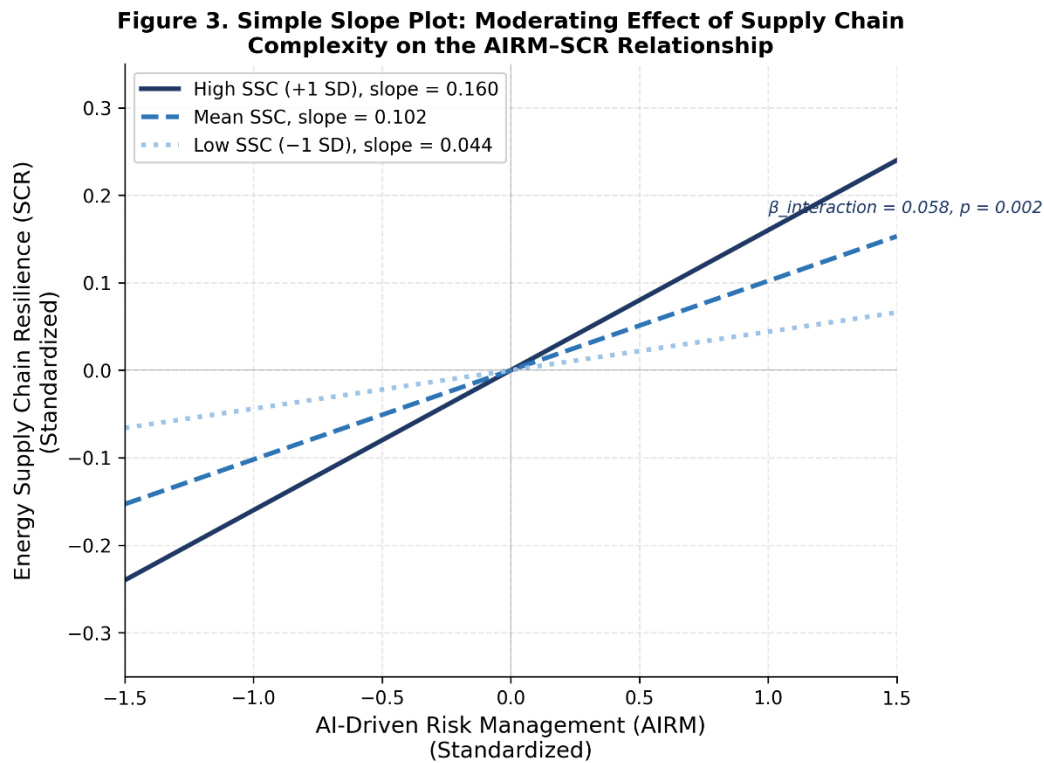


Fig.3: Simple Slope Plot: Moderating Effect of Supply Chain Complexity between AIRM–SCR

## 6. Discussion

The results indicate a statistically significant positive association between AI-driven risk management and energy supply chain resilience in Jordan's energy sector, providing support for H1. Although the effect size is relatively small ( $\beta = 0.102$ ), the finding is meaningful both theoretically and practically. From a theoretical perspective, the findings are consistent with dynamic capabilities theory in an emerging economy energy context, suggesting that AI may function as an enabling infrastructure supporting sensing, seizing, and reconfiguring capabilities associated with organizational resilience. In comparison with prior studies conducted in manufacturing and retail contexts (Belhadi et al., 2024; Dey et al., 2024), the present findings suggest that AI-related capabilities such as disruption prediction, real-time information processing, and scenario-based logistics planning may also be relevant within energy supply chains, which are characterized by high interdependence, regulatory complexity, and cascading disruption risks. The modest effect size ( $f^2 = 0.089$ ) should not be interpreted as evidence of AI's limited value. Rather, it reflects the multifactorial nature of resilience in energy systems, where AI is one of several enabling conditions alongside institutional governance, infrastructure quality, and human capital readiness. This interpretation aligns with Jordan's energy context specifically, where the sector is undergoing digital transformation while continuing to face legacy infrastructure constraints, high import dependency, and evolving regulatory frameworks. In this setting, AI-driven risk management may represent a potentially valuable mechanism for improving information visibility and logistics coordination across energy networks, although its effectiveness appears likely to depend on complementary structural and organizational capabilities, as reflected in the moderation findings.

The positive moderating association of supply chain complexity ( $\beta = 0.058, f^2 = 0.042$ ) provides support for H2 and represents an important theoretical contribution of this study. The findings suggest that supply chain complexity may strengthen the positive relationship between AI-driven risk management and resilience, indicating that the relationship varies across different structural conditions. This pattern is consistent with the directional hypothesis and aligns with dynamic capabilities theory, which proposes that sensing and reconfiguring capabilities may become increasingly valuable under

conditions of higher information-processing demands and structural complexity (Modgil et al., 2022; Belhadi et al., 2024).

In Jordan's energy sector specifically, supply chain complexity takes a distinctive form shaped by four contextual realities. First, the country's heavy reliance on energy imports, historically exceeding 90% of total energy consumption, creates multi-tier supplier networks spanning multiple geopolitical risk zones (Schuetze & Hussein, 2023). Second, the ongoing renewable energy transition, with solar and wind capacity expanding rapidly, introduces new logistics coordination demands across distributed generation, transmission, and distribution nodes (Al-Shetwi, Atawi, El - Hameed, & Abuelrub, 2025). Third, regulatory heterogeneity across conventional and renewable energy subsectors creates information asymmetries that AI-based systems are well positioned to resolve (Saeed, 2025). Fourth, regional geopolitical instability, including proximity to conflict zones, is expected to increase disruption probability and elevate the strategic value of real-time risk intelligence (Alshwawra & Almuhtady, 2020). Together, these contextual factors may help explain why higher levels of complexity are associated with a stronger relationship between AI-driven risk management and resilience within Jordan's energy supply chains. The findings also contribute to logistics and informatics research by suggesting that information complexity, process interdependence, and network breadth may shape the conditions under which AI-related capabilities become more relevant within energy logistics systems. From a theoretical standpoint, this study contributes to the dynamic capabilities literature by suggesting that the relationship between AI-driven digital capabilities and resilience may be contingency-dependent, with supply chain complexity acting as a relevant contextual condition. This interpretation extends prior discussions of technology-enabled resilience by incorporating structural network characteristics into the analysis of AI-related resilience outcomes. It also contributes to logistics and informatics research by indicating that AI-driven risk management may support information visibility, logistics coordination, and service system responsiveness within energy networks, rather than functioning solely as a generic operational tool.

From a practical standpoint, the findings offer specific implications for energy sector managers and policymakers in Jordan and comparable emerging economies. Three concrete recommendations follow from the results. First, AI investment in energy supply chains should prioritize tools that directly address information visibility and real-time coordination, specifically predictive analytics platforms for fuel supply disruption forecasting, IoT-enabled logistics monitoring for transmission and distribution networks, and AI-driven decision support systems for renewable energy dispatch optimization. Second, supply chain complexity should be managed strategically rather than minimized uniformly. Given the observed moderating relationship, energy firms may benefit from strengthening data governance frameworks, system interoperability standards, and inter-organizational collaboration mechanisms that support the effective use of AI within complex supply chain environments. Third, policymakers in Jordan should align the national digital transformation agenda with energy supply chain design by establishing data-sharing protocols across energy subsectors, investing in cybersecurity infrastructure for critical energy logistics nodes, and developing regulatory frameworks that support AI-driven risk management across both conventional and renewable energy supply chains. Overall, the findings suggest that supply chain complexity may increase the practical relevance of AI-driven risk management within energy logistics systems.

## **7. Conclusion**

This study examined the relationship between AI-driven risk management and energy supply chain resilience in Jordan's energy sector while also investigating the moderating role of supply chain complexity. Drawing on dynamic capabilities theory, the study offers sector-specific empirical insights from an emerging economy context where digital transformation is ongoing and supply chain complexity is structurally significant. The findings indicate a positive and statistically significant association between AI-driven risk management and energy supply chain resilience, with the relationship being associated with improvements in information visibility, real-time logistics coordination, and disruption sensing capabilities across energy networks.

It is important to clarify, however, that the study measures and interprets resilience, defined as the ability to anticipate, absorb, and recover from supply chain disruptions, as the primary outcome. While resilience is a foundational enabler of sustainable energy systems, sustainability itself, encompassing environmental performance, carbon reduction, and long-term resource stewardship, is a downstream implication of the findings rather than a directly tested construct. This distinction is intentional because the study focuses specifically on resilience-related organizational capabilities and coordination mechanisms, while the broader relationship between AI-driven resilience and sustainability outcomes remains an avenue for future empirical investigation. In the Jordanian context, where energy security remains strategically important, these findings may offer relevant insights for policymakers and industry practitioners involved in digital transformation initiatives.

This study contributes to the literature in two main ways. First, the findings suggest that the relationship between AI-driven digital capabilities and resilience may be contingent on structural supply chain conditions, particularly supply chain complexity. This interpretation extends existing discussions of technology-enabled resilience by incorporating structural network characteristics into the analysis. Second, the study contributes to logistics and informatics research by indicating that AI-driven risk management may be associated with resilience through mechanisms related to real-time data processing, predictive logistics coordination, and service system responsiveness. For decision-makers and energy managers in Jordan and similar contexts, the findings underscore that AI adoption must be accompanied by investment in data governance infrastructure, system interoperability standards, and supply chain design capabilities to realize the full resilience benefits of digital transformation.

The study is subject to several limitations that should be considered when interpreting the findings. First, the cross-sectional research design captures a single point in time and cannot establish causal dynamics or track how AI adoption and resilience co-evolve over time. Second, the single-country focus on Jordan, while theoretically motivated, limits the generalizability of findings to other emerging economy energy contexts with different institutional and infrastructural conditions. Third, the reliance on self-reported perceptual data from a single respondent per organization introduces the potential for common method bias, which was assessed but not entirely eliminated through procedural remedies. Fourth, the model is intentionally parsimonious, including only three constructs and one interaction term. Important variables discussed in the literature, including digital maturity, data governance quality, cybersecurity capability, and human-AI collaboration dynamics, were not directly measured and may represent omitted variables that shape the AI-SCR relationship. Fifth, the study does not directly measure sustainability outcomes, and the link between AI-driven resilience and environmental or social sustainability performance remains an empirically open question. Future studies should tackle these gaps using longitudinal design, multi-country comparative studies, and extended models that incorporate digital maturity, institutional quality, and sustainability outcomes as additional constructs. Ultimately, the findings suggest that the effectiveness of AI-related initiatives in Jordan's energy sector depends not only on technological investment, but also on implementation quality, governance readiness, and coordination capabilities across supply chain networks.

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