“Employing artificial intelligence to improve the supply chain’s resilience and performance: Moderating the impact of supply chain dynamics”

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EMPLOYING ARTIFICIAL INTELLIGENCE TO IMPROVE THE SUPPLY CHAIN'S RESILIENCE AND PERFORMANCE: MODERATING THE IMPACT OF SUPPLY CHAIN DYNAMICS

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Abstract

The study aims to explore the direct and indirect effects of artificial intelligence on resilience and performance in a modern supply chain evolution environment. The email survey reached 208 companies from Jordan registered with the Jordanian Industry and Commerce, and results were collected using structural equation modeling analysis. The results show the impact of artificial intelligence on overall supply chain performance. However, similar output is only achievable using its equipage capability to return data to promote the resilience of supply and performance. This paper provides additional standpoints on how to use artificial intelligence to ensure supply chain performance; however, longitudinal research offers deeper insights. Furthermore, this analysis addresses the existing gap in the literature regarding synthetic intelligence. While this study has taken critical measures throughout the research process to ensure safety, it is necessary to note that it is still susceptible to some common boundaries found in survey designs. A longitudinal study might expand the research to examine further aspects of the phenomenon.

Keywords COVID-19, artificial intelligence, visibility, sourcing, performance

JEL Classification M11, M15, L23

INTRODUCTION

The fast transmission of COVID-19 has challenged various governments' ability to contain its distribution. Even after many efforts from different governments, public institutions, and other businesses to reduce its effect on health and the economy, the consequences of the COVID-19 pandemic are still felt across the globe. The pandemic has resulted in fatalities and disrupted the supply chain in numerous sectors, impacting the performance of enterprises. Multiple businesses across the globe were severely affected. They have openly discussed the difficulties they encounter in adapting their distribution networks. Companies unprepared for supply chain disruptions like COVID-19 experienced delays in deliveries from certain locations due to inadequate information. However, they attribute the current shortages to factors like supplier consolidation, manufacturing cost reductions, and risk mitigation strategies. Acknowledging the challenges in present-day supply chains that have led businesses to this state of distress is essential. The manufacturing process has become highly complex by sourcing components from different locations to create a product. Consequently, there is a reliance on logistics, imports, and exports.

This dependency raises concerns during disruptions, highlighting the importance of making decisions. Sourcing organizations also encounter obstacles related to distribution risks and network shortages.

Amid COVID-19, managing warehouses through direct distribution and responsive allocation have become aspects of the distribution sector. The retail supply chains have felt the impact, too, witnessing an uptick in demand for goods but a decrease in the popularity of luxury items. Such shifts pose threats to profit margins and existing business models. The unprecedentedly high demand levels for COVID-19 consumer goods and over-the-counter medications have pushed the dependency on supply networks to its limit, making it difficult to control the changing demand and supply patterns. In addition, artificial intelligence integrates capabilities to develop systems based on genetic algorithms, agents, and expert systems, which can process consumer demand, incoming orders, network optimization, supplier system integration, and inventory control. The outbreak of COVID-19 has prompted organizations to reevaluate and revamp their supply chain strategies. Scriffignano (2020) revealed that 75% of businesses in industries like services, manufacturing, wholesale, and retail are associated with economies like China that have suffered significant negative impacts from the pandemic. To sum up, COVID-19 has exposed vulnerabilities within supply chains.

1. LITERATURE REVIEW

1.1. Artificial intelligence

Over the past two decades, many companies have worked on digitizing their operations, leading to the growth of a thriving industry. Artificial intelligence has been recognized as a technology that enables communication between machines (Toorajipour et al., 2021). However, Guzman and Lewis (2019) argued that its potential lies in improving supply chain efficiency by addressing challenges and managing large amounts of data. In addition, Guzman and Lewis (2019) confirmed that artificial intelligence is not a concept; its value in applications such as supply chain management has only recently gained recognition. By providing decision-making abilities to tackle issues, artificial intelligence can elevate supply chain performance by ensuring timely and flawless deliveries, thus boosting customer satisfaction. Implementing artificial intelligence can simplify compliance processes, cut costs, and enhance the efficiency of a supply chain network (Treleaven & Batrinca, 2017). Moreover, Huang and Rust (2021) argued that artificial intelligence enhances capabilities essential for demand forecasting in today's ever-changing business landscape. Customizing interactions with artificial intelligence-powered chatbots can also improve customer communication effectiveness (A. Alzoubi & M. Alzoubi, 2020). With the help of automated assistants backed by feedback from users and customer service representatives, they can aid in tracking the delivery status of a product (Grover et al., 2020).

1.2. Supply chain resilience

Amid the challenges posed by the COVID-19 outbreak, the focus on supply chain resilience has intensified among top-level executives. Supply chain resilience pertains to the ability of supply chains to effectively manage and recover from disruptions. Adobor (2020) argued the conceptual framework for extending an understanding of resilience in complex adaptive systems (CAS), such as supply chains, using the adaptive cycle framework. The study confirmed that supply chain resilience aims to restore or even enhance operational performance levels post-disruption, as emphasized by Ponomarov and Holcomb (2009). The evaluation of supply chain resilience occurs in three phases during a disruption: preparedness (actions before a disturbance), response, and recovery following the event. This concept originates from studies that emphasize restoring equilibrium after events. Wong et al. (2020) examined the relationship between business values for supply chain resilience under different types and levels of disruptions. However, the global impact of COVID-19 has introduced the idea of resilience. This new perspective suggests that intricate supply networks may not return to a state but require ongoing adaptation and learning in response to disruptions, as noted by Wong et al. (2020). According to Ponomarov and Holcomb (2009), resilient supply networks are less susceptible to disruptions and can manage supply chain interruptions. Supply chain resilience enables businesses to ensure the supply of their products and services to customers (Kano &

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Oh, 2020). Research on supply chain resilience has expanded significantly since the pioneering work by Christopher and Pecks (2004). Nevertheless, De Sá et al. (2020) and Sundarakani et al. (2021) note that there is more to be achieved in terms of establishing how supply chain resilience develops, owing to progress and the shifting dynamics of supply networks.

1.3. Supply chain collaboration

Collaboration within the supply chain entails liaising with organizations in the supply chain to achieve mutual benefit (Baryannis et al., 2019). However, de Sá et al. (2020) investigate how resilience at different nodes in the supply chain influences overall supply chain resilience (SCRES) during an extreme weather event. This study found that in a supply chain with low interdependence among players, individual firm resilience elements might be preferable to interorganizational ones. Supply chain partners share risks and rewards to establish trust, strengthen relationships, and decrease risks (Rajesh, 2020; Belhadi et al., 2022). Enhancing supply adaptability and minimizing scarcity necessitate having flexibility in all sorts of agreements, including long-term and short-term agreements. In the current paper, the obtainable literature on building links, encouraging resource exchange through link interactions, and providing entry to the supply of resources, both tangible and intangible, between organizations within the supply chain is discussed (Scholten et al., 2014; Lohmer et al., 2020).

1.4. Supply chain risk management culture

Creating a culture centered around managing risks in the supply chain involves implementing practices to identify and manage risks across all levels of the organization to ensure that everyone embraces this approach (de Sá et al., 2020). Belhadi et al. (2024) examined the direct and indirect effects of AI, SCRES, and Supply Chain Performance (SCP) under the context of dynamism and uncertainty of the supply chain. The study conceptualized the use of artificial intelligence (AI) in the supply chain based on organizational information processing theory. The results showed that while AI has a direct impact on SCP in the short term, it is recommended that its information processing capabilities be exploited to build SCRES for long-lasting SCP. This includes forming a risk management team, cultivating a culture focused on managing risks, and raising awareness among all staff members (De Sá et al., 2020; Belhadi et al., 2022). Numerous studies have highlighted the importance of understanding the structure of supply chains, encompassing both informational components. This understanding is vital for enhancing adaptability to changes and providing education for individuals and organizations (Rostami et al., 2020).

1.5. Supply chain performance

Prior studies have provided evidence showing that intelligence technology could increase businesses' performance by improving collaboration and interactions between supply chains and customers through improved supply chain management (Altay et al., 2018; Sabahi & Parast, 2020). Supply chains that apply artificial intelligence technology to pricing and demand prediction reduce their losses by more than 56% in cases where they suffer from "out of stock" situations (Dubey et al., 2020). Additionally, the technology improves the inspection of a product. Similarly, integrating artificial intelligence into recommendation systems when advertising improves the return on investment. When applied to customer relationship management, consumers find such businesses accommodating (Lima-Junior & Carpinetti, 2020). However, Modgil et al. (2022) examined how firms employ AI and consider the opportunities for AI to enhance supply chain resilience by developing visibility, risk, sourcing, and distribution capabilities. Also, it bridges the gap between businesses and their customers. Supply chain performance is crucial as it indicates how well a company's supply chain operations manage costs and meet customer needs effectively (Adobor, 2020; Modgil et al., 2022). Artificial intelligence technology has potential across business sectors such as order fulfillment, customer relations management, demand forecasting, procurement processes, inventory management, and purchasing decisions. This study expects businesses leveraging artificial intelligence technology to see impacts on supply chain efficiency (Sabahi & Parast, 2020; Sharma, 2020).

1.6. Information processing capabilities

Artificial intelligence is the process by which a system learns from data in its surroundings to adjust and come up with strategies. This involves methods and procedures that help one gain knowledge from input data, even if one does not know the expected output formats beforehand. The field of artificial intelligence has gone through periods of growth and decline since it first emerged in the 1950s (Belhadi et al., 2022). It is due to technology's advances in computing power, the amount of data used, and the integration of artificial intelligence into operations and supply chain management that this technology has piqued scientists' interest (Belhadi et al., 2024). Belhadi et al. (2022) examined how the open design of 3D printed mobile phone accessories helps overcome size-related resource constraints, facilitate market growth, and ultimately generate sufficient consumer demand to alter the market leaders' supply chain practices in favor of social sustainability. Moreover, scientists have suggested identifying the processing potential of artificial intelligence systems using three tasks and categories of stages within the information processing theory, including exploiting, expanding, and exploring (Belhadi, 2021). These stages also describe the influence artificial intelligence systems may have on decision-making.

Based on the literature review on artificial intelligence in supply chain management, when complying with these stages with the most commonly used methodologies (Beltagui et al., 2020), one may categorize them as follows. Firstly, the following methodologies are employed in the phase of exploration: machine learning and big data, optimization, fuzzy logic and programming, Statistical programming, and knowledge representation reasoning (Baryannis et al., 2019; Cavalcante et al., 2019; Sabet et al., 2020). They allow for overcoming limitations in information processing, having control over datasets, and identifying patterns. Furthermore, the innovative methodologies used involve exploration and leveraging (Schniederjans et al., 2020; Dhamija & Bag, 2020). They help develop ideas to substantially improve human-machine interaction as issue analysis progresses. Thus, the methodologies used may include network-based algorithms and tree-based clustering. The methods include artificially intelligent exploration algorithms, such as agent-based systems, model predictive control, robotic process automation, and computer vision (Baryannis et al., 2019; Mehdizadeh, 2020).

1.7. Dynamic capabilities

Firm resources form the basis for improving a company's abilities, ultimately leading to its edge (Grant, 1991). This gives rise to capabilities that determine a firm's ability to quickly adapt to changing business conditions. This adjustment happens through aligning external resources (Teece et al., 1997). Dynamic capabilities refer to a company's capacity to intentionally create, expand, or modify its resource pool (Huang & Rust, 2021). These competencies can be either internal or external and closely linked to resilience capabilities in the supply chain field (Dubey et al., 2020). First, data centers allow the identification, analysis, and mitigation of risks by enabling resources and skills that ensure the business remains relevant in the rapidly changing environment. In the supply chain, data centers function as knowledge processing and engineering systems and tools that enhance, protect, and extend trading networks to create more value for customers (Kwak et al., 2018). The role of distributional centers is increasingly popular in supply chains due to increasing network complexity. What value can the company form, what is its ability to deliver, and what role and implications of its essential capabilities and skills play in improving its competitive advantages and position, especially in securing a long-term sustainable competitive advantage?

The COVID-19 pandemic highlighted the effectiveness of distribution centers in enhancing supply chain resilience and ensuring the continued viability of an organization amidst uncertainty. Kwak et al. (2018) investigated the relationship between supply chain innovation, risk management capabilities, and competitive advantage in global supply chains. They found that innovative supply chains have a discernible positive influence on all dimensions of risk management capability, which in turn has a significant impact on enhancing competitive advantage. However, some previous research has extensively studied artificial intelligence but has not focused

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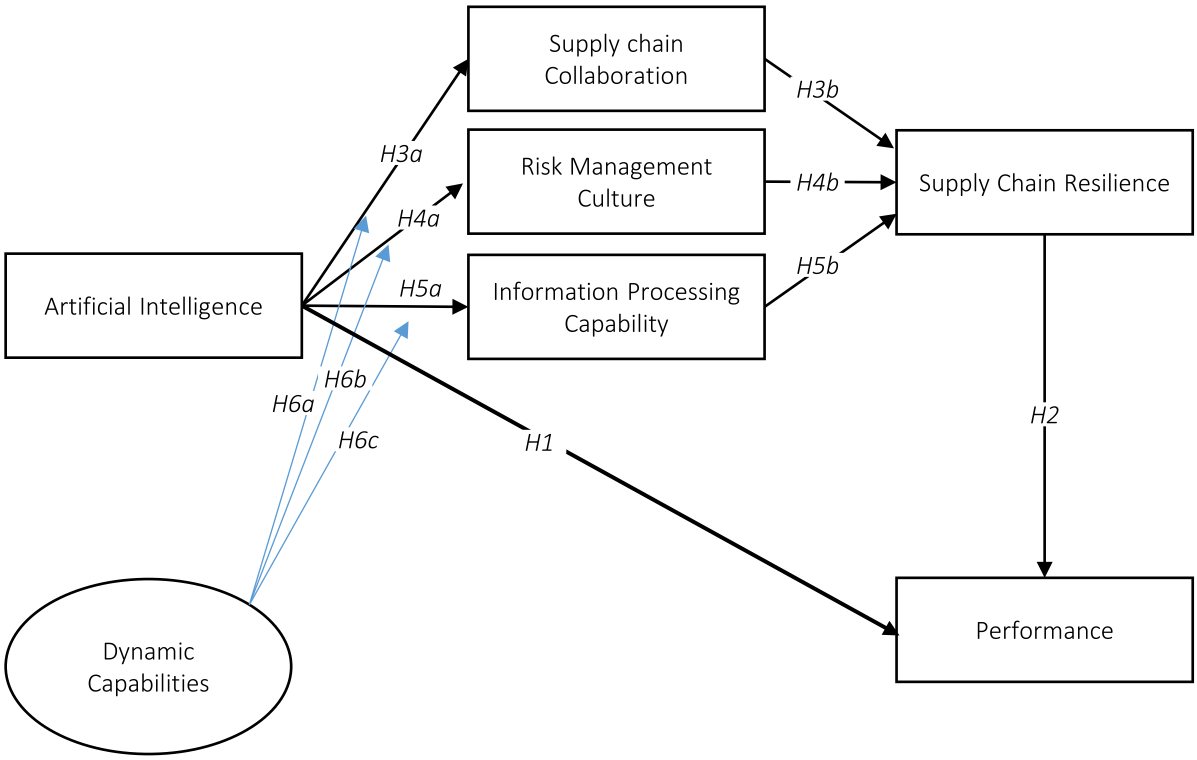

Figure 1. Research framework

on its application in the supply chain domain (Ponomarov & Holcomb, 2009; Schniederjans et al., 2020). Therefore, there is a need to explore the implementation of artificial intelligence and draw insights from the experiences during the COVID-19 outbreak to enhance supply chain management practices.

Figure 1 illustrates a model that displays the suggested links between the variables along with the proposed study hypotheses.

H1: Artificial intelligence has a significant impact on supply chain performance.

H2: Supply chain resilience has a significant impact on supply chain performance.

H3a: Artificial intelligence has a significant impact on supply chain collaboration.

H3b: Supply chain collaboration has a significant impact on supply chain resilience.

H4a: Artificial intelligence has a significant impact on supply chain risk management culture.

H4b: Supply chain risk management culture has a significant impact on supply chain resilience.

H5a: Artificial intelligence has a significant impact on information processing capabilities.

H5b: Information processing capabilities have a significant impact on supply chain resilience.

H6a, b, c: Dynamic capabilities have a positive moderating impact on the association between (a) artificial intelligence and supply chain collaboration, (b) artificial intelligence and risk management culture, and (c) artificial intelligence and information processing capabilities.

2. METHOD

The study delves into how multinational supply chains are evolving through the adoption of artificial intelligence technology. The study focuses on analyzing a company as the subject. This study interviewed a key representative from the company to gain insights into the study's concepts using a custom tool for a participant to ensure precision. The study identified a total of 268 managers and senior executives from advanced companies in Jordan. This analysis focused specifically on engaging individuals in the implementation of artificial intelligence in supply chain operations. Surveys (Appendix A) were distributed to these individuals via email. The survey package included a questionnaire along with a cover letter detailing the research objectives, data usage intentions, and assurances of data confidentiality. After conducting two rounds of data collection over eight weeks and sending three follow-up emails, 208 usable responses were retrieved. This yielded a response rate of 68.28%, which aligns well with the response rates observed in studies (Belhadi et al., 2024).

Following the guidance of Malhotra and Grover (1998), this study adapted existing measurement tools, from research-making tweaks to the wording of the questions, to suit the specific research context and insights gained from an initial test. Survey questions were rated on a five-point Likert scale. This study conducted a response bias assessment using Armstrong and Overton's (1977) methodology to address bias in the survey approach. This involved comparing responses from participants (25% of respondents), late participants (25% of respondents), and a sample of individuals who did not respond to the survey. The analysis of this study revealed that for all questions, the p-value exceeded 0.1, indicating no differences among early, late, and non-respondents. Thus, this means that non-response bias is not an issue in this study.

3. RESULTS

Several experiments were conducted to determine the accuracy and reliability of the measurement method. Cronbach's alpha was utilized to assess the consistency and dependability of the survey. Following the guidelines by Hair et al. (2017), a threshold of 0.70 was applied. Table 1 shows Cronbach's alpha coefficients for each subscale of the scale, all exceeding the threshold of 0.70. Fornell and Larcker (1981) suggest a threshold of 0.70 for the construct reliability (CR) test and 0.50 for the variance extracted (AVE) test to evaluate a measuring instrument's convergent validity. It is important to note that while component failure rates in Table 1 fell short of requirements, route loadings for each component exceeded 0.50, indicating relationships. The validity of hypotheses within the research framework was assessed.

Table 1. Measurement model

Factors	Loading	CA	CR	AVE
Artificial intelligence	0.789	0.902	0.909	0.898
	0.711			
	0.801			
	0.841			
	0.755			
Collaboration	0.824	0.924	0.889	0.771
	0.814			
	0.854			
	0.847			
Risk management culture	0.710	0.886	0.922	0.891
	0.707			
	0.706			
	0.715			
Information processing capabilities	0.735	0.933	0.866	0.844
	0.737			
	0.739			
	0.729			
Resilience	0.775	0.875	0.822	0.923
	0.752			
	0.766			
Performance	0.820	0.915	0.919	0.819
	0.827			
	0.816			
	0.852			
Dynamic capabilities	0.825	0.942	0.933	0.942
	0.863			
	0.822			
	0.854			

The discriminant validity test is a key test that helps identify if a concept supports its own indicators in the PLS path model (Hair et al., 2017). The validity of measurement models is typically assessed using the Fornell–Larcker criteria. As per the Fornell–Larcker criterion, it is recommended that the square root of the variance extracted by a construct be greater than the correlation between the construct and all the other constructs (Hair et al., 2017). This method was chosen because it has proven to be an effective technique for identifying validity issues utilizing the heterotrait-monotrait ratio of the correlation approach (Modgil et al., 2022). The HTMT results in Table 2 show that the measurement model reflects the validity of the studied construct (A. Alzoubi & M. Alzoubi, 2020). All the values are below the recommended maxi-

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mum of 0.85, pointing toward validity among the constructs. The indicator relationships with the concept possess stronger correlations than the indicator relationships in the same construct. These findings indicate distinctions between ideas without similarities.

Table 2. Discriminant validity

Construct	AI	SCC	RMC	IPC	SCR	SCP	DC
AI	0.526						
SCC	0.510	0.468					
RMC	0.522	0.519	0.603				
IPC	0.544	0.449	0.602	0.629			
SCR	0.642	0.441	0.549	0.676	0.674		
SCP	0.639	0.515	0.533	0.658	0.515	0.587	
DC	0.631	0.417	0.541	0.672	0.599	0.597	0.491

Note: AI = Artificial intelligence; SCC = Collaboration; RMC = Risk management culture; IPC = Information processing capabilities; SCR = Resilience; SCP = Performance; DC = Dynamic capabilities.

This study used the Fornell–Larcker criteria to assess its validity. This criterion is considered met when the correlations between components are lower than the average variance extracted (AVE) from those components. The square roots of AVEs highlighted for emphasis show values compared to component correlations. This finding offers evidence supporting the effectiveness of the analysis. After validating the measurement model, the study analyzed the model, achieving an R^2 score of 63.3%. The R^2 value surpasses Hair et al.'s (2017) 30% threshold. The standardized path coefficients and p-values presented in Table 5 offer an explanation for the variability observed in endogenous components. The framework explained variance (R^2) for supply chain cooperation stands at 0.70, while risk management culture is at 0.67, information processing capability is at 0.73, and supply chain resilience is at 0.75. The relationships between intelligence and performance ($\beta = 0.58$; $p < 0.000$) and supply chain resilience and performance ($\beta = 0.61$; $p < 0.000$) demonstrate outcomes according to path coefficients and p-values, leading to support for H1 and H2. Factors such as supply chain collaboration, risk management culture, and information processing capabilities influence the impact of intelligence on supply chain resilience. Specifically, artificial intelligence positively affects collaboration (with a coefficient of 0.52 and a p-value < 0.000), which in turn enhances resilience (coefficient of 0.59; $p < 0.000$). The relationship between intelligence and risk management culture is also significant, with a coefficient of 0.57 and a p-value < 0.000. Similarly, the connection between risk management culture and resilience shows a correlation with a coefficient of 0.61 and a p-value < 0.000. Furthermore, the study highlights the association between intelligence and information processing capacities (coefficient of 0.65; $p < 0.000$). It was also observed that information processing capabilities positively correlate with resilience (coefficient of 0.67; $p < 0.000$). These results confirm H3a and H3b, H4a and H4b, and H5a and H5b.

The analysis supports H6a, H6b, and H6c, indicating that dynamic capabilities play a role in influencing the connections between intelligence and collaboration within supply chains ($\beta = 0.42$; $p < 0.000$), intelligence and fostering a culture of risk management ($\beta = 0.48$; $p < 0.000$), artificial intelligence and enhancing information processing abilities ($\beta = 0.41$; $p < 0.000$), as well as artificial intelligence and overall performance ($\beta = 0.51$; $p < 0.000$).

Table 3. Hypotheses results

Hypotheses	β	T	P	Decision
H1	0.58	4.365	0.000	Supported
H2	0.61	4.227	0.000	Supported
H3a	0.52	6.187	0.000	Supported
H3b	0.59	6.161	0.000	Supported
H4a	0.57	5.336	0.000	Supported
H4b	0.61	6.202	0.000	Supported
H5a	0.65	3.523	0.000	Supported
H5b	0.67	3.253	0.000	Supported
H6a	0.42	5.445	0.000	Supported
H6b	0.48	4.578	0.000	Supported
H6c	0.41	5.245	0.000	Supported

4. DISCUSSION

The study explored a framework that links intelligence, supply chain collaboration, risk management culture, information processing capabilities, supply chain resilience, performance, and dynamic capabilities. The findings suggest that leverag-

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ing intelligence methods could help supply chains improve their performance during disruptions by enhancing information processing and adaptability. However, these studies have not adequately assessed the extent of this impact on various intelligence inferences (Altay et al., 2018; Akter et al., 2020). As revealed by Baryannis et al. (2019), the information processing capacity affects performance in an organization. This study, therefore, examines the relationship between artificial intelligence-driven information processing capacity and creativity, variability, and long-run performance in contexts of supply chain management characterized by uncertainty and variability (Belhadi et al., 2024).

It is concluded that artificial intelligence innovations have the potential to help firms in changing environments and maintaining or improving their performance. Artificial intelligence can make decisions by learning from data, prompting supply chain innovation, and responding rapidly to incidents (Cavalcante et al., 2019; Dubey et al., 2020; Belhadi et al., 2024). The robust connection between supply chain resilience and performance can also be ascertained. The firms that have access in advance of an incident respond effectively to it throughout the occasion, and quickly cure it thereafter are again much more likely to prosper. The results align with Belhadi et al. (2024) and Akter et al. (2020).

In light of the above, it is important to implement a long-term perception to encourage performance in intelligence. Thus, one may decide to boost capability in readiness and recovery (Mahajan & Tomar, 2021). However, one knows which amount of assistance from leveraging information processing and innovation could strengthen preparedness, recovery, and trigger and heal from actions and developments, which can finally improve long-term performance (Akter et al., 2020). The gap in the studies can thus be explained by an identified view of artificial intelligence in the literature as a technical device that just changes the preparedness measures (Lima-Junior & Carpinetti, 2020). De Sá et al. (2020) and Toorajipour et al. (2021) have demanded the role of companionship collaboration in forming the capacity to sustain the gang when organizing culture and critical weaknesses when collaboration autonomously consumes important information capacities.

The key to the study was established by combining artificial intelligence with innovation effects, which were artificial intelligence-driven innovation influence and the advancement of processing skills. This finding portrays significant positive development dynamics in how artificial intelligence influences all these factors. The findings are consistent with the studies carried out by Scholten et al. (2014), Cavalcante et al. (2019), and Sabahi and Parast (2020). Artificial intelligence-driven innovation proficiencies work to powerfully reiterate the potential for the firm's travel to frame its long-term fluency. Businesses that strengthen artificial intelligence models with the ability of informatics to foster collaboration with self-grown algorithms that change roundabouts and learn from their behavior can coordinate to withstand disturbances. Due to its chances with forthcoming occurrences, they share their judgments on inventories and productivity activities in actual time (de Sá et al., 2020; Rajesh, 2020; Sabet et al., 2020). Artificial intelligence is also a learning system and artificial intelligence-enabled enterprises' judgments can communicate in the most straightforward way possible should a spell hold or provide a prompt risk due to an approaching incident and alter their tactics (Dubey et al., 2020). Hence, they can provide in an affair and help their supplier or clients when a partner happens using artificial intelligence decision mechanisms. Additionally, the relationship between artificial intelligence and intelligence and its links to inventories can be said to affirm belief or suggest a much wider range of artificial intelligence success. In other words, there are even further factors and questions (Baryannis et al., 2019). The way organizations contribute to the growth of organizational skills, such as information handling, is shaped by the elusive disposition of the past arrangement and management parameters; the connection is the natural expansion of a linear movement, and the end has multiplied into a situation with disastrous results. All of these must be considered together in revealing, and all invoke the current field's merged theoretical understanding and businesses to certain questions (Mehdizadeh, 2020; Queiroz et al., 2022).

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CONCLUSION

The aim was to determine the impact of synthetic intelligence-primarily based systems on improving overall performance in the presence of dynamism and uncertainty, both without delay and indirectly. The paradigm was then subjected to empirical evaluation using facts gathered from 208 businesses of varying sizes, situated in many places around Jordan and functioning in diverse monetary sectors. The findings offer empirical proof that supports the proposed framework. This evidence shows that the record-processing talents of artificial intelligence have a sizeable impact on overall performance. This effect may be visible either through the development of associated metrics or through the introduction of lengthy-term overall performance via strengthening the resilience of the delivery chain. Developing synthetic intelligence abilities is essential for companies to achieve sustained overall performance by enhancing supply chain resilience. This may be done through supply chain collaboration, hazard management culture, and data processing skills, which are the principal enablers in the dynamic and uncertain delivery chain environment.

Furthermore, this paper addresses the prevailing gap within the literature, referring to the topic of synthetic intelligence. While this paper has carried out critical measures throughout the study process to ensure safety, it is essential to observe the risks of a few boundaries regularly seen in survey designs. Moreover, the consequences of this look provide an image of a selected moment in time, which is similarly emphasized through the present-day urgency to address the COVID-19 pandemic. Therefore, it is vital to conduct comprehensive longitudinal research to validate the connections among artificial intelligence, resilience, and overall performance in the post-COVID-19 age.

Furthermore, while this study covers a diversity of industries, it is crucial to note that each company analyzed functions within the production industry. To generalize the consequences of this research, it is important to conduct comparable studies in other spheres, including travel, transportation, and healthcare.

AUTHOR CONTRIBUTIONS

Conceptualization: Adnan Taha, Sarwar Khawaja, Fayyaz Qureshi, Firas Rashed Wahsheh.
Data curation: Adnan Taha, Sarwar Khawaja, Fayyaz Qureshi, Firas Rashed Wahsheh.
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Investigation: Adnan Taha.
Methodology: Sarwar Khawaja, Firas Rashed Wahsheh.
Project administration: Adnan Taha.
Resources: Fayyaz Qureshi.
Writing – original draft: Adnan Taha, Fayyaz Qureshi, Firas Rashed Wahsheh.
Writing – review & editing: Sarwar Khawaja, Firas Rashed Wahsheh.

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APPENDIX A

Table A1. Questionnaire

Factors	Items
Artificial intelligence	How familiar are you with the concept of artificial intelligence (AI) in the context of supply chain management?
	Have you implemented any AI solutions in your supply chain operations to address the challenges posed by COVID-19? If yes, please provide details.
	Do you believe that AI can help improve the resilience and performance of your supply chain in the context of COVID-19? Why or why not?
	In what specific ways do you think AI can mitigate the impact of COVID-19 on supply chain operations?
	How do you envision integrating AI technologies into your existing supply chain processes to address COVID-19 challenges?
Collaboration	How would you rate the level of collaboration among your supply chain partners before and during the COVID-19 pandemic?
	In what specific ways has collaboration with supply chain partners influenced the resilience of your supply chain during COVID-19?
	How has collaboration with supply chain partners impacted the overall performance of your supply chain during the COVID-19 pandemic?
	To what extent do you think collaboration with other supply chain partners has influenced the availability and quality of data for AI-driven analytics during COVID-19?
Risk management culture	In what ways does your organization's risk management culture influence the overall performance of your supply chain during the COVID-19 pandemic?
	How do you measure the effectiveness of risk management practices in improving supply chain performance?
	Do you believe that a strong risk management culture enhances the effectiveness of AI solutions in addressing COVID-19 challenges within the supply chain? Why or why not?
	How do you think a risk-aware culture within supply chain operations can facilitate the implementation and integration of AI technologies?
Information processing capabilities	Do you believe that strong information processing capabilities enhance the effectiveness of AI solutions in addressing COVID-19 challenges within the supply chain? Why or why not?
	How would you rate the information processing capabilities of your supply chain before and during the COVID-19 pandemic?
	In what ways does the information processing capability of your supply chain affect its overall performance during the COVID-19 pandemic?
	How do you measure the effectiveness of information processing in improving supply chain performance?
Resilience	How would you define resilience within your supply chain context?
	What are the main challenges your organization has faced in building resilience within the supply chain, particularly in response to COVID-19?
	In what ways do you think AI technologies can enhance the resilience of your supply chain?
Performance	What are your expectations for the future role of performance management in supply chain operations post-COVID-19?
	How do you address these challenges, and what strategies have you implemented to improve supply chain performance?
	In what specific ways do you think AI technologies can improve the performance of your supply chain?
	How would you define performance within your supply chain context?
Dynamic capabilities	How would you define dynamic capabilities within the context of your supply chain?
	How do you assess the dynamic capabilities of your supply chain, particularly in response to the challenges brought by COVID-19?
	What key elements or components do you consider essential for building dynamic capabilities within your supply chain?
	In what specific ways do you think AI technologies can enhance the dynamic capabilities of your supply chain?

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