Open Journal of Business and Management, 2024, 12, 4340-4358
https://www.scirp.org/journal/ojbm
ISSN Online: 2329-3292
ISSN Print: 2329-3284

Does Supply Chain Resilience Mediate the Relation between Artificial Intelligence Capabilities and Supply Chain Performance?

Gladys Tuo[1], Michael Karikari Appiah[2], Kwame Owusu Sarpong[1], Stephen Okyere[1]

[1]Department of Procurement and Supply Chain Management, Kumasi Technical University, Kumasi, Ghana
[2]School of Sustainable Development, University of Environment and Sustainable Development, Somenya, Ghana
Email: gladys.tuo@kstu.edu.gh, makarikari@yuesd.edu.gh, kosarp1@gmail.com, Stephen.okyere@kstu.edu.gh

How to cite this paper: Tuo, G., Appiah, M. K., Sarpong, K. O., & Okyere, S. (2024). Does Supply Chain Resilience Mediate the Relation between Artificial Intelligence Capabilities and Supply Chain Performance? *Open Journal of Business and Management, 12,* 4340-4358.
https://doi.org/10.4236/ojbm.2024.126218

Received: October 17, 2024
Accepted: November 18, 2024
Published: November 21, 2024

Abstract

Undisputedly, low-income economies are saddled with unique growth obstacles, such as increased vulnerability to external shocks, limited infrastructure, and low technological applications, amongst other constraints. This study presents new contributions on how to enhance supply chain performance in the emerging market from the perspective of Artificial Intelligence (AI) capabilities and resilience supply chain in Ghana where such studies predominantly remain fuzzy. This paper aims to develop a model to explain how the integration of AI capabilities could enhance supply chain resilience to improve the supply chain performance of low-resource economies. This study has been approached using a quantitative research strategy and comprehensive survey design. Data have been collected from a cross-section of medium and large-scale manufacturing companies from Ghana between April and July 2023. The data analyses and hypotheses were tested using the Variance-based Structural Equation Modelling Technique and SMART-Partial Least Square version 3.8.9. The indicative results have shown that AI capabilities (tangible resources, human resources, and intangible resources) have a positive and significant relationship with supply chain resilience and supply chain performance. Besides, supply chain resilience has a positive and significant relationship with supply chain performance. Again, supply chain resilience positively and significantly mediates the relationship between AI capabilities and supply chain performance. The implications of the paper include the development of a theoretical framework in a low-income context that integrates AI capabilities, supply chain resilience, and supply chain performance. The outcomes of the paper offer unique guidance for business owners, practitioners, trade facilitators, and regulators on how to implement AI capabilities to enhance supply chain performance.

Keywords

Artificial Intelligence Capabilities, Low-Income Economics, Resilience Supply Chain, Supply Chain Performance

1. Introduction

Undoubtedly, low-income economies are saddled with unique growth obstacles, such as increased vulnerability to external shocks, limited infrastructure, and low technological applications, amongst other constraints. This study presents new contributions on enhancing supply chain performance in the global market from the perspective of Artificial Intelligence capabilities (AIC) and resilience supply chain in Ghana, where such studies predominantly remain fuzzy. AI capability entails the ability of a company to select, organize, and deploy AI-specific resources (Paschen et al., 2019; Wamba-Taguimdje et al., 2020; Alter, 2022). AIC further involves the ability of a company to organize and deploy computer systems capable of executing business tasks by performing processes that are quite similar to human processes, such as learning, reasoning, and self-correction (Mikalef et al., 2019; Naz et al., 2023; Gama and Magistretti, 2023; Wang et al., 2023). AI is used in various applications, including healthcare, agriculture, aviation, law, and manufacturing. In addition, AICs are systems that exhibit intelligent behaviour by analyzing their environment and acting autonomously to achieve specific goals. AICs also refer to machines that perform cognitive functions typically associated with humans, such as learning, communication, problem-solving, and creativity (Yuhas, 2017; Rai et al., 2019; Gama and Magistretti, 2023; Kumar et al., 2023). One of the main propositions of the current study is that AICs improve supply chain, supply chain performance. Thus, AICs provide the enablers to build a resilient supply chain capable of enhancing the overall performance of supply chain performance (Gama and Magistretti, 2023; Kumar et al., 2023).

Sequel to the above, supply chain resilience (SCR) encompasses the ability of supply chain networks to withstand disruptions and minimize the impact of shocks on revenues, costs, and customers. SCR can be used as a tool to reduce supply chain risks and vulnerabilities and competitive resilience as an organizational capability that provides a competitive advantage (Adobor and McMullen, 2018; Modgil et al., 2022; Ozdemir et al., 2022; Rahman et al., 2022). In addition, SCR is the ability of an organization to rapidly respond to and recover from supply chain disruptions without significantly impacting the production or delivery of products. SCR is defined as the ability of a system to return to its initial state within an acceptable timeframe after disruptions. SCR also entails the level of business continuity, connectivity, structure, and supply chain resilience required to prepare for, respond to, and recover from supply chain disruptions (Aslam et al., 2020; Li et al., 2020; Han et al., 2020). For example, Abou-Foul et al. (2023) analyzed the nature and adoption role of the link between AI and service competencies. They found that the service-learning pathway not only involves the development of AI competencies related to the optimization of internal processes and resources but also identifies AI as an added competence for social innovation services. Chowdhury et al. (2023) also conducted a multidisciplinary literature review and reaffirmed that adopting AI capabilities comes with associated benefits.

This paper aims to examine the implications of AI capabilities and supply chain resilience on supply chain performance and to develop a model to explain how integrating AI capabilities could enhance supply chain resilience to improve the supply chain performance of low-resource economies. The paper will contribute diversely to existing theories, practices, and policies by addressing these objectives. The paper is among the paucity of extant studies to consider supply chain resilience as a mediator in the relationship between AI capabilities and supply chain performance (Drydakis, 2022; Abou-Foul et al., 2023; Chowdhury et al., 2023). In this light, the paper contributes to a context-specific framework involving how supply chain resilience mediates the supply chain of low-resource and emerging economy contexts. Further, the paper contributes a broader understanding of AI capabilities and how they could be integrated into supply chains of emerging economies to augment supply chain performance.

Moreover, it has developed a framework in a low-income context that integrates AI capabilities, supply chain resilience, and supply chain performance, which could be used to design organizational strategies and regulatory frameworks. Also, policymakers will be informed on the essence of facilitating supply chain resilience through reassuring policies and regulations that support the adoption and implementation of AI technologies. Finally, the paper's outcomes offer unique guidance for business owners, practitioners, trade facilitators, and regulators on how to implement AI capabilities to enhance supply chain performance. To maximize the aforementioned contributions, the paper addresses the research questions below (RQ): RQ1: What is the relationship between AI capabilities and supply chain resilience? RQ2: What is the relationship between AI capabilities and supply chain performance? RQ3: Does supply chain resilience mediate the relationship between AI capabilities and supply chain performance in an emerging economy? RQ4: How does supply chain resilience influence supply chain performance?

This report is structured into five sections as follows: The opening section presents the background objectives and contributions of the paper; the second section presents the literature reviews with a focus on theoretical, empirical, and hypotheses development; the third section presents the research methodology, the fourth section presents the results and discussions, and the final section presents the conclusions, implications, and limitations of the study.

2. Literature Review and Hypotheses Development

2.1. Theoretical Review

The main theoretical underpinning for the study is dynamic capability theory, which is supplemented by the resource-based view theory. Dynamic capability theory entails an organization's ability to integrate, create, and transform internal and external resources/capabilities to respond to and shape a rapidly changing business environment (Teece et al., 1997, 1990). Dynamic capability may be based on specific change processes (e.g., product development at a particular stage of development) or analysis (e.g., investment decisions) but more often on creative leadership and entrepreneurship (e.g., entry into new markets). Dynamic capability reflects the speed and extent to which an organization's internal resources and capabilities adapt to the opportunities and demands of the business environment. Firms with strong dynamic capability may experience abnormal returns because the market does not value capability according to its value to the buyer when it has other, more significant, jointly owned assets. The paper argues that for AI capabilities to be integrated into existing supply chain systems operated by medium and large-scale Ghanaian manufacturing companies, there is a need to sense the presence or influx of AI technologies, learn about the AI technologies, and finally, reconfigure the AI into the existing processes. The essence of resources/capabilities and dynamic capabilities is that they usually cannot be bought but must be created. These capabilities are necessary to ensure long-term profitability (Teece, 2007).

Moreover, the resource-based view theory is used to explain the role of supply chain resilience. Resilience is treated as an intangible resource that is unique, rare, and immobile, serving as a firm's comparative advantage (Barney, 1990). Inferring from the dynamic capability theory assumptions, the framework, as illustrated in Figure 1, has been developed to guide the study.

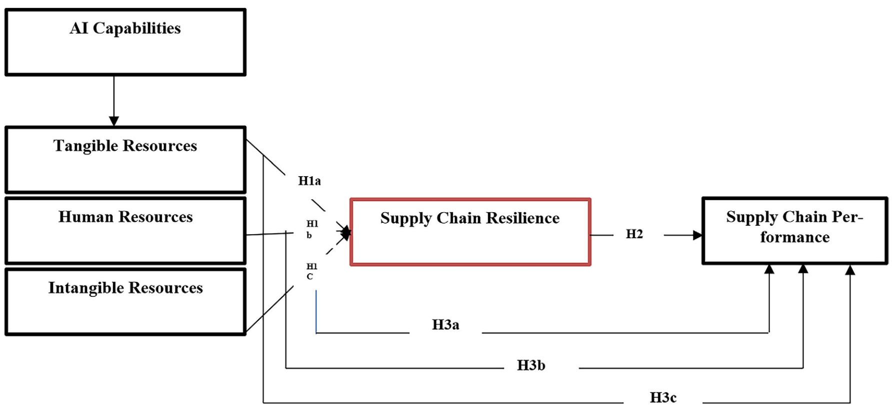

Figure 1. Research framework.

2.2. Artificial Intelligence Capabilities (AIC) and Supply Chain Resilience

Arguing from the point of dynamic capability theory, artificial intelligence capability enhances supply chain resilience which will subsequently affect supply chain performance, because AI can foster more active knowledge sharing, manifested in an organizational culture characterized by good teamwork, consistent common goals and shared resources (Pereira and Mohiya, 2021; Alter, 2022; Drydakis, 2022; Abou-Foul et al., 2023; Chowdhury et al., 2023). Artificial intelligence acts intelligently, analyzing its environment and following formal rules to achieve its goals. AIC capability defines how much an organization can use and manage specific artificial intelligence resources (Mikalef and Gupta, 2021). Furthermore, AIC refers to the ability of innovation teams to develop AI-based machines that mimic human cognitive functions and perform tasks such as problem-solving and intelligent learning (Elia et al., 2018; Salehi and Burgueño, 2018).

With artificial intelligence, organizations are agile Data warehousing, rapid data processing technology and implementation of advanced algorithms, and reinvestment in technologies that facilitate data sharing (Pandey et al., 2021). In addition, AIC also requires long-term relationships between departments and a strong knowledge-sharing culture within the organization (Bughin et al., 2017). AIC can improve compliance and risk management activities and contribute to financial risk management through a better understanding of data and the use of rapid automated data analysis (Yigit and Kanbach, 2021). The paper argues that adopting AI technologies enables manufacturing firms to analyze customer data, identify customer needs, identify business opportunities, and improve the innovation team's ability to design and commercialize new service innovations that meet customer needs. Therefore, the following hypotheses have been proposed:

H1a-c: AI capabilities (tangible resources, human resources, and intangible resources) will significantly affect supply chain resilience

2.3. Supply Chain Resilience (SCR) and Supply Chain Performance

Another cardinal assumption of this paper is that resource-based view theory could be used to explain the relationship between supply chain resilience and firm performance. Because SCR can adjust production capacity, modify quantities, adjust product design, adapt quickly, integrate different promotional activities, and manage supply fluctuations (Yuan and Beatrice, 2012; Biedermann & Kotzab, 2019; Alonso-Muñoz et al., 2021). In addition, SCR entails the ability of the supply chain to prepare for and respond rapidly to unexpected risk events, recover from potential disruptions and return to a baseline state, or transition and develop to a new, more desirable state to improve customer service, market share, and financial performance (Tukamuhabwa et al., 2017; Adobor and McMullen, 2018; Kopanaki et al., 2018; Ferreira et al., 2021). Again, resilient supply chains must be responsive to the market, as they must understand and respond to demand while minimizing the risk of shortages and supply disruptions (Kochan and Nowicki, 2018; Pires Ribeiro and Barbosa-Povoa, 2018). Payyoli (2022) posited that SCR is the ability of a supply chain network to withstand disruptions and minimize their impact on revenues, costs, and customers and further added that SCR has to do with a company's ability to leverage its existing capabilities to cope with unexpected supply chain disruptions (Aslam et al., 2020; Li et al., 2020; Han et al., 2020). In sum, the paper argues that manufacturing companies with robust supply chain resilience will have the capacity to maintain or re-establish a stable dynamic state that enables them to continue operating after a disaster or under conditions of continuing stress while maintaining or improving their performance. Therefore, the following hypothesis has been proposed:

H2: Supply chain resilience will significantly affect supply chain performance.

2.4. Supply Chain Resilience (SCR) as a Mediator between AI Capabilities and Supply Chain Performance

The SCR of a firm is the inherent ability of an organization (system) to maintain or re-establish a stable dynamic state that enables it to continue operating after a disaster or under conditions of ongoing stress. Inferring from the resource-based view and the dynamic capability theories, the paper argues that firms that adopt and adapt AI technologies enhance their supply chain resilience and subsequently improve their supply chain performance. Supply chain performance refers to the efficiency with which each stage of the e-commerce supply chain optimizes costs, reduces inefficiencies, enhances speed, and meets customer expectations (Maestrini et al., 2017; Mishra et al., 2018; Hove-Sibanda and Pooe, 2018; Reddy et al., 2019; Nandi et al., 2020; Wamba et al., 2020; Hallikas et al., 2021; Gupta et al., 2021). Specifically, supply chain performance includes meeting end-customer requirements, including the availability of products, on-time delivery, and all required inventory, as well as the supply chain's ability to respond to this performance. Additionally, it could refer to the ability of the entire supply chain to meet end-customer requirements through product availability and responsiveness to delivery times. Improving supply chain performance is a continuous process and requires both an analytical performance measurement system and an operational mechanism to achieve the key performance indicator targets (Trisnawati and Pujawan, 2021; Teke et al., 2022; Özkanlısoy and Bulutlar, 2023). SC performance includes the optimization of integration between suppliers, manufacturers, warehouses, and depots to ensure that products are produced and distributed in the right quantities, at the right place, and at the right time, minimizing costs and ensuring satisfaction (Flora, 2022; Rasool et al., 2022).

Meanwhile, the SCR of a firm re-establishes a stable dynamic state that enables it to continue operating after a disaster. The paper argues that firms that adopt and adapt AI technologies enhance their supply chain resilience and subsequently improve their supply chain performance. Therefore, the following hypothesis has been proposed:

H3a-c: Supply chain resilience will significantly mediate the relationship between AI capabilities (tangible resources, human resources, and intangible resources) and supply chain performance.

3. Research Methodology

3.1. Research Approach, Strategy, and Design

This study has been approached using a quantitative research method, explanatory strategy, and comprehensive survey design. The quantitative method has been utilized to explain how integrating AI capabilities could enhance supply chain resilience to improve the supply chain performance of low-resource economies because it involves measuring quantifiable and observable outcomes. Moreover, quantitative research includes applications of mathematical and statistical models in problem-solving and knowledge-acquisition processes. Again, the quantitative approach method is consistent with the explanatory research strategy, which seeks to explain the causes and effect relationship between exogenous and endogenous variables employed in the research model. For instance, the current study investigates how many changes could be caused by AI capabilities to affect supply chain resilience and performance. Therefore, employing the explanatory strategy to complement the quantitative approach is imperative.

3.2. Research Population and Sampling Technique

The population of this paper comprises medium- and large-scale manufacturing companies in Ghana. The main inclusion criteria employed in the selection of the companies' study include 1) Firms that are registered with the registrar general department with a certificate of incorporation and commencement, 2) Firms that have operated for over 3 years, 3) Firms that are wholly owned and managed by Ghanaians, 4) Firms that have accepted to sign the inform consent and willingly participate in the study and finally, the company must be a number of one of these regulatory bodies or other recognized one: Ghana Chamber of Commerce and Industry, Ghana Enterprise Agency, and Association of Ghana Industries. These groups were chosen because they predominantly meet the criteria for selecting the study's participants. Even though small and micro enterprises dominate the industry, they are largely unregistered and do not keep formal records of their operations. In each of the selected firms, 5 individuals were targeted. These include operations managers, procurement/supplier officers, accountants/finance officers, business owners, and inventory managers. These requirements were flexible to the variations in job designations among the companies. The estimated population of the study was estimated at 950. The sample size was determined using Taro Yamane's (1970) statistical formula at a 95 percent confidence interval and 0.05 or 5 percent error term. From the estimate, 284 sample size was the minimum sample size required for the study. Meanwhile, 385 sample size was used in the study.

3.3. Data Collection Method, Sources of Measurement Instruments, and Common Method Bias

The study used a structured questionnaire consistent with the comprehensive survey design. Questionnaires are cost-effective, have wide coverage, and are time-effective. The instruments have been adopted from prior studies and improved to meet the objectives and the demand. For instance, measures for AI capabilities were adopted from Wang et al. (2023), measures for supply chain resilience were adopted from Ozdemir et al. (2022), and supply chain performance was adopted from Hove-Sibanda and Pooe (2018). The questionnaire has been structured into two parts: The first part sought to profile the firms in terms of size (number of employees), firm stability (number of years businesses have operated), and job designation. The second part of the questionnaire focused on AI capabilities, supply chain resilience, and supply chain performance. Data have been collected from a cross-section of medium and large-scale manufacturing companies from Ghana between April and July 2023. The questionnaires were administered to the respondents face-to-face and online (Google Forms). The online survey was chosen because most companies did not have time during normal working hours and opted for an online survey. Over 600 questionnaires were administered, but 405 were returned. Subsequently, the 405 responses were scrutinized to obtain 385 usable responses, representing a 93.5 percent response rate. As part of the measures to avoid common method bias, the instrument was pretested with 30 responses. The 30 responses reflect 10 percent of the sample size; as suggested by Saunders et al. (2007), 10 percent of a given sample size is suitable for pretesting the survey measurements. The essence of the pretesting was to assess the extent of validity and reliability of the measurement instruments. This exercise informed the rewording of some of the survey items. Also, issues of double barren questions were also addressed. Finally, the questions were kept simple and free from all forms of ambiguity. Again, the instruments went through three different categories of validations. Namely, content validity, face validity, and construct validity. Colleagues and Lecturers from other universities were consulted to validate the questionnaire.

3.4. Data Analyses and Hypotheses Testing

The data analyses and hypotheses were tested using the Variance-based Structural Equation Modelling (SEM) Technique and SMART-Partial Least Square version 3.8.9. SEM has been used in the study because it's a second-generational tool for analyzing multiple relationships simultaneously. For instance, in SEM analysis, there is no such thing as dependent and independent variables; only endogenous and exogenous variables exist. Every construct could be independent or dependent at any time. The SEM analyses have been structured into three parts: The first part of the SEM analysis deals with the measurement model, which focuses on construct validity (convergent and discriminant validities). The second part of the analysis deals with structural modelling, which deals with path coefficients and hypotheses testing. The mediation analysis was conducted by duly following Hair et al. (2017) procedure for mediation analysis using the bootstrapping technique. The final section presents the Construct Cross-validated Redundancy scores.

4. Results and Discussions

4.1. Results

Table 1 presents the results of descriptive statistics (mean, median, maximum, minimum, standard deviations), normality (skewness and Kurtosis), and Variance Inflatory Factor (VIF). The results showed that the majority of the participants somewhat agreed with the various statements in the survey instrument with a degree of variations as reflected in the means and standard deviation scores (Mean scores exceeding 3.0 and some standard deviations exceeding are greater than one). Again, Kurtosis and skewness values are within the ranges of normality. Skewness and Kurtosis are within the range of −2 to +2. The VIF scores are < 5.

Table 1. Descriptive statistics, normality test and Variance Inflatory Factor (VIF).

	Mean	Median	Min	Max	Std. Deviation	Kurtosis	Skewness	VIF
HS1	3.876	4.000	1.000	5.000	0.970	1.090	−0.997	2.895
HS2	3.938	4.000	1.000	5.000	0.875	0.129	−0.558	3.211
HS3	3.749	4.000	1.000	5.000	1.024	−0.751	−0.483	2.466
HS4	3.881	4.000	1.000	5.000	1.001	0.052	−0.733	1.721
HS5	3.822	4.000	1.000	5.000	0.956	−0.236	−0.568	2.009
INT1	3.811	4.000	1.000	5.000	0.993	−0.174	−0.645	4.901
INT2	3.819	4.000	1.000	5.000	1.009	0.410	−0.866	3.232
INT4	3.851	4.000	1.000	5.000	0.960	0.289	−0.730	2.444
INT5	3.878	4.000	1.000	5.000	0.938	−0.308	−0.584	2.487
SCP1	3.811	4.000	1.000	5.000	0.987	−0.034	−0.679	3.145
SCP1	3.754	4.000	1.000	5.000	1.081	−0.426	−0.567	3.732
SCP2	3.824	4.000	1.000	5.000	0.983	0.423	−0.841	3.189
SCP3	3.738	4.000	1.000	5.000	1.029	−0.284	−0.564	2.470
SCP4	3.735	4.000	1.000	5.000	1.045	−0.079	−0.638	2.490
SCP5	3.673	4.000	1.000	5.000	1.092	−0.659	−0.510	4.382
SCP6	3.651	4.000	1.000	5.000	1.100	−0.626	−0.498	4.264
SCR2	3.824	4.000	1.000	5.000	1.029	−0.457	−0.555	3.719
SCR3	3.827	4.000	1.000	5.000	0.971	−0.132	−0.643	5.500
SCR4	3.868	4.000	1.000	5.000	0.948	0.394	−0.745	1.933
SCR5	3.859	4.000	1.000	5.000	0.943	−0.195	−0.611	4.187
TA2	3.800	4.000	1.000	5.000	0.999	−0.218	−0.636	4.502
TA3	3.800	4.000	1.000	5.000	1.004	0.188	−0.780	4.138
TA4	3.835	4.000	1.000	5.000	0.977	0.661	−0.870	4.049
TA5	3.838	4.000	1.000	5.000	0.962	0.145	−0.695	4.551
TA1	3.846	4.000	1.000	5.000	1.000	−0.271	−0.598	1.817

Note: TA: Tangible Resources, HS: Human Resources, INT: Intangible Resources. SCP: Supply Chain Performance and SCR: Supply Chain Resilience.

4.1.1. Measurement Model (Convergent and Discriminant Validities)

The first part of the SEM analysis deals with the measurement model, which focuses on construct validity. To address issues of convergent validity in the model, four different tests have been conducted. Notably, CA = Cronbach's Alpha, CR = Composite Reliability, AVE = Average Variance Extracted, and factor (item) loadings. For the model to meet the required convergence CA should be 0.70 or better, CR should be 0.70 or better, AVE should be 0.50 or better, and item loading must be 0.70 or better. As shown in **Table 2** and **Figure 2**, all the tests have exceeded the minimum required scores for convergence validity. For instance, CA scores and CR scores far exceed 0.70. Besides, AVE scores ranged between 0.762 and 0.558, exceeding the minimum requirement of 0.50. Therefore, the study has met the requirement for convergent validity.

On the other hand, two main tests have been conducted to assess the discriminant validity of the study. Namely, using the squared root of AVEs (Fornell and Lacker, 1981) criteria and Heterotrait-Monotrait (HTMT) Ratio (Hohenstein et al., 2015).

Table 2 shows that the squared AVEs are greater than the highest score for the inter-constructs' correlation. Again, the HTMT scores, as shown in **Table 3**, ranged between 0.287 and 0.753.

Table 2. Discriminant validity and reliability using Fornell & Larcker (1981) criterion.

	CA	rho_A	CR	AVE	HS	INT	SCP	SCR	TA
HS	0.863	0.871	0.901	0.646	**0.804**				
INT	0.895	0.894	0.927	0.762	0.258	**0.873**			
SCP	0.840	0.848	0.876	0.541	0.362	0.268	**0.736**		
SCR	0.799	0.816	0.861	0.558	0.305	0.288	0.756	**0.747**	
TA	0.915	0.923	0.936	0.747	0.264	0.258	0.745	0.756	**0.864**

CA = Cronbach's Alpha, CR = Composite Reliability, AVE = Average Variance Extracted; TA: Tangible Resources, HS: Human Resources, INT: Intangible Resources. SCP: Supply Chain Performance and SCR: Supply Chain Resilience. NB: The square root of the AVE is indicated in the diagonal.

Table 3. Heterotrait-Monotrait Ratio (HTMT).

	HS	INT	SCP	SCR	TA
HS					
INT	0.304				
SCP	0.436	0.301			
SCR	0.374	0.347	0.697		
TA	0.297	0.287	0.753	0.767	

Note: TA: Tangible Resources, HS: Human Resources, INT: Intangible Resources. SCP: Supply Chain Performance and SCR: Supply Chain Resilience.

4.1.2. Structural Model (Path Coefficients and Hypotheses Testing)

Table 4 presents the predictive power and predictive relevance of the model; the results showed that the model's predictive power ranged between 73 to 74 percent,

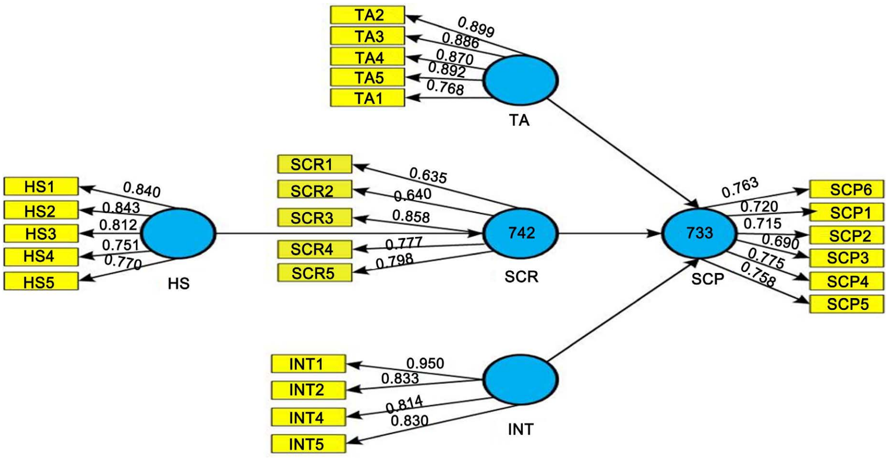

Figure 2. Items loadings and r-square scores.

suggesting a strong predictive model. The Q-square results further indicate that the model is relevant because the Q-square scores are greater than zero. As indicated in Table 4, the results from the path coefficients have shown that there is a significant and positive relationship between HS and SCR (β = 0.074, t-statistics = 2.545, *p*-values < 0.011). Therefore, H1 is supported. Again, there is a significant and positive relationship between INT and SCR (β = 0.057, t-statistics = 1.973, *p*-values < 0.049). Therefore, H2 is supported. Also, there is a significant and positive relationship between SCR and SCP (β = 856, t-statistics = 73.681, *p*-value < 0.000). Therefore, H3 is supported. More so, a significant and positive relationship exists between TA and SCR (β = 0.822, t-statistics = 38.623, *p*-value < 0.000). Hence, H4 is supported. Proceeding to the indirect effect, SCR significantly mediates the relationship between HS and SCP (β = 0.063, t-statistics = 2.547, *p*-values < 0.011). Therefore, H5 is supported. Further, SCR significantly mediates the relationship between INT and SCP (β = 0.049, t-statistics = 1.975, *p*-value < 0.049). Therefore, H6 is supported. Also, SCR significantly mediates the relationship between TA and SCP (β = 0.703, t-statistics = 29.270, *p*-values < 0.000). Therefore, H7 is supported. The path coefficients, as shown in Figure 3, further confirm that all the hypotheses are supported in the new model.

Table 4. Hypotheses testing and path coefficients.

	Hypothesis	Original Sample	Sample Mean	Std. Deviation	T Statistics	*p* Values
	Direct Effect					
H1	HS -> SCR	0.074	0.075	0.029	2.545	0.011
H2	INT -> SCR	0.057	0.058	0.029	1.973	0.049
H3	SCR -> SCP	0.856	0.858	0.012	73.681	0.000
H4	TA -> SCR	0.822	0.822	0.021	38.623	0.000
	Indirect Effect					
H5	HS -> SCR -> SCP	0.063	0.064	0.025	2.547	0.011

Continued

H6	INT -> SCR -> SCP	0.049	0.049	0.025	1.975	0.049
H7	TA -> SCR -> SCP	0.703	0.705	0.024	29.270	0.000

Note: TA: Tangible Resources, HS: Human Resources, INT: Intangible Resources. SCP: Supply Chain Performance and SCR: Supply Chain Resilience.

Table 5. Construct cross-validated redundancy and r-square (Adj.R^2).

	SSO	SSE	Q^2 (= 1 − SSE/SSO)	R^2	Adjusted R^2
HS	1850.000	1850.000			
INT	1480.000	1480.000			
SCP	2220.000	1441.205	.351	0.733	0.732
SCR	1850.000	1101.685	.404	0.742	0.740
TA	1850.000	1850.000			

Note: TA: Tangible Resources, HS: Human Resources, INT: Intangible Resources. SCP: Supply Chain Performance and SCR: Supply Chain Resilience.

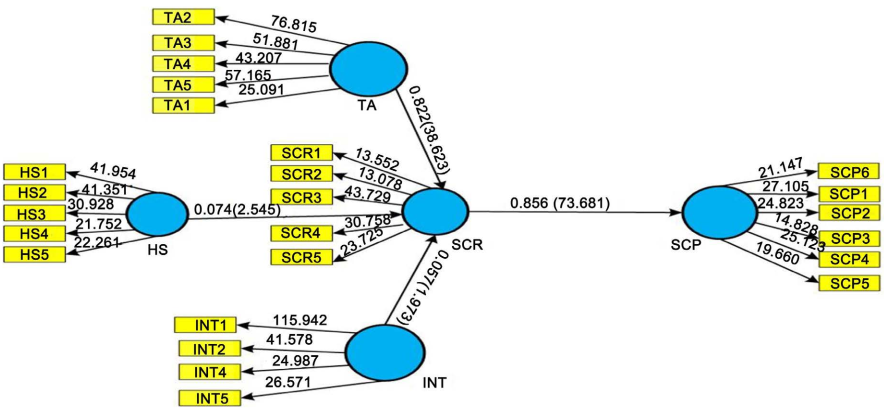

Figure 3. T-values and path coefficients.

4.2. Discussion

It is a known fact that low-income economies are saddled with unique growth obstacles, such as increased vulnerability to external shocks, limited infrastructure, and low technological applications, amongst other constraints. This study has presented new contributions to enhancing supply chain performance in the emerging market from the perspective of artificial intelligence capabilities and the resilience of the supply chain in Ghana, where such studies predominantly remain fuzzy.

The study has revealed that AI capabilities (tangible resources, human resources, and intangible resources) have a positive and significant relationship with supply chain resilience and supply chain performance. Besides, supply chain resilience has a positive and significant relationship with supply chain performance. These results are empirically supported (Alter, 2022; Drydakis, 2022; Abou-Foul et al., 2023; Chowdhury et al., 2023; Gama and Magistretti, 2023; Kumar et al., 2023; Naz et al., 2023; Gama and Magistretti, 2023; Wang et al., 2023). For instance, Abou-Foul et al. (2023) investigated the nature of the relationship between AI performance, services, and the role of absorptive capacity using SEM and fuzzy set comparative qualitative analysis (fsQCA). They found that AI capability impacts services and absorptive capacity. In addition, developing AI capabilities related to internal process and resource optimization combined with AI for social innovation services provides pathways to service delivery. Again, Wang et al. (2023) proposed a model of how AI in higher education affects student learning outcomes and found that AI competency in higher education is a three-level variable composed of three second-order formative variables, including resources (data, technology, key resources), skills (technical skills, educational applications, collaboration skills), and attitudes (reform, innovation awareness); AI competency in higher education has a significant impact on students' self-efficacy and creativity; AI competency in higher education affects student learning outcomes.

Moreover, Naz et al. (2023) examined the relationship between big data analytic capabilities (BDAC) and artificial intelligence capabilities to find out how the two constructs can work together to enhance performance. They found that environmental dynamics as a mediator has a positive and significant effect on BDAC and CIN but no significant effect on AIC and CIN. Finally, environmental dynamics have a positive and significant mediating effect on hotel BDAC and CIN performance, while AIC and co-innovation do not significantly affect hotel performance. More so, Drydakis (2022) examined whether the application of artificial intelligence (AI) is related to the reduction of entrepreneurial risk in SMEs and found that AI enables SMEs to enhance their dynamic capabilities through technology.

Again, supply chain resilience positively and significantly mediates the relationship between AI capabilities and supply chain performance. Besides, the paper has developed a theoretical framework in a low-income context that integrates AI capabilities, supply chain resilience, and supply chain performance. These results are consistent with previous related studies (Aslam et al., 2020; Li et al., 2020; Han et al., 2020; Modgil et al., 2022; Ozdemir et al., 2022; Rahman et al., 2022). Modgil et al. (2022) used artificial intelligence (AI) to improve supply chain resilience to extreme disruptions such as COVID-19. They reported that AI supply chains support the systematic development of the sustainability of their structures and networks. As resilient supply chains in dynamic environments and extreme failure scenarios, they are able to quickly identify operations (risk identification, failure levels, failure triangles, trend data), analyze (what-if scenarios, realistic customer requirements, simulated extreme conditions, and extreme tests), reconfigure (automation, network reconfiguration, monitoring, threat control. and physical security efforts) and enable (business rules application, contingency management, emergency management, physical security management) and enable (business rules application, emergency management, physical security management).

4.3. Conclusions and Implication

4.3.1. Conclusion

In an attempt to enhance the supply chain performance by addressing growth obstacles such as increased vulnerability to external shocks, limited infrastructure, and low technological applications, this paper aims to examine the implications of AI capabilities and supply chain resilience on supply chain performance and develop a model to explain how the integration of AI capabilities could enhance supply chain resilience to improve supply chain performance. The study has revealed that AI capabilities (tangible resources, human resources, and intangible resources) have a significant relationship with SCR and SC performance. Again, SCR has a significant relationship with supply chain performance. Again, supply chain resilience positively and significantly mediates the relationship between AI capabilities and supply chain performance. The paper concludes that AI capabilities are essential in building a resilient supply chain and improving the overall supply chain performance of the low-resource and emerging economy context. (Abou-Foul et al., 2023; Chowdhury et al., 2023; Kumar et al., 2023; Naz et al., 2023; Gama and Magistretti, 2023; Wang et al., 2023).

4.3.2. Implications-Theoretical, Practical, and Policy

The paper's implications include the development of a theoretical framework in a low-income context that integrates AI capabilities, SCR, and SC performance. The paper is among the paucity of extant studies that consider supply chain resilience as a mediator in the relationship between AI capabilities and supply chain performance. In this way, the paper contributes to a context-specific framework involving how supply chain resilience mediates the supply chain of low-resource and emerging economy contexts. In this light, the paper contributes a broader understanding of AI capabilities and how they could be integrated into emerging economies' supply chains to augment supply chain performance. Moreover, it has developed a framework in a low-income context that integrates AI capabilities, SCR, and supply chain performance, which could be used to design organizational strategies and regulatory frameworks. Also, policymakers will be informed on the essence of facilitating supply chain resilience through reassuring policies and regulations that support adopting and implementing AI technologies. Again, the paper's outcomes offer unique guidance for business owners, practitioners, trade facilitators, and regulators on implementing AI capabilities to enhance SC performance.

5. Limitations and Suggestions for Future Studies

The study has limitations, including a choice of design, scope, and time horizon. The current study has utilized a quantitative research approach based on the research paradigm adopted. Meanwhile, future studies should consider other approaches, such as mixed methods and qualitative approaches. Also, future studies should consider different scopes apart from those of manufacturing companies. It is strongly recommended that a comparative study between local manufacturing companies and transnational corporations be conducted. Again, longitudinal studies should be considered in future studies to establish the trends in AI capabilities. More so, further studies could be considered in the future to detailly assess the dimensions of the AI capabilities. Moreover, moderating variables should be considered in any future studies to strengthen the proposed model.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

References

Abou-Foul, M., Ruiz-Alba, J. L., & López-Tenorio, P. J. (2023). The Impact of Artificial Intelligence Capabilities on Servitization: The Moderating Role of Absorptive Capacity-A Dynamic Capabilities Perspective. *Journal of Business Research, 157,* Article ID: 113609. https://doi.org/10.1016/j.jbusres.2022.113609

Adobor, H., & McMullen, R. S. (2018). Supply Chain Resilience: A Dynamic and Multidimensional Approach. *The International Journal of Logistics Management, 29,* 1451-1471. https://doi.org/10.1108/ijlm-04-2017-0093

Alonso-Muñoz, S., González-Sánchez, R., Siligardi, C., & García-Muiña, F. E. (2021). New Circular Networks in Resilient Supply Chains: An External Capital Perspective. *Sustainability, 13,* Article 6130. https://doi.org/10.3390/su13116130

Alter, S. (2022). Understanding Artificial Intelligence in the Context of Usage: Contributions and Smartness of Algorithmic Capabilities in Work Systems. *International Journal of Information Management, 67,* Article ID: 102392. https://doi.org/10.1016/j.ijinfomgt.2021.102392

Aslam, H., Khan, A. Q., Rashid, K., & Rehman, S. (2020). Achieving Supply Chain Resilience: The Role of Supply Chain Ambidexterity and Supply Chain Agility. *Journal of Manufacturing Technology Management, 31,* 1185-1204. https://doi.org/10.1108/jmtm-07-2019-0263

Barney, J. B. (1990). The Debate between Traditional Management Theory and Organizational Economics: Substantive Differences or Intergroup Conflict? *Academy of Management Review, 15,* 382-393. https://doi.org/10.5465/amr.1990.4308815

Biedermann, L., & Kotzab, H. (2019). Erfolgsfaktoren zur zukünftigen Gestaltung resilienter Supply Chains—Konzeption eines Bezugsrahmens. In C. Bode, R. Bogaschewsky, M. Eßig, R. Lasch, & W. Stölzle (Eds.), *Supply Management Research* (pp. 235-254). Springer Fachmedien Wiesbaden. https://doi.org/10.1007/978-3-658-23818-6_11

Bughin, J., Hazan, E., Ramaswamy, S., Chui, M., Allas, T., & Dahlström, P. (2017). *Artificial Intelligence: The Next Digital Frontier?* McKinsey Global Institute.

Chowdhury, S., Dey, P., Joel-Edgar, S., Bhattacharya, S., Rodriguez-Espindola, O., Abadie, A. et al. (2023). Unlocking the Value of Artificial Intelligence in Human Resource Management through AI Capability Framework. *Human Resource Management Review, 33,* Article ID: 100899. https://doi.org/10.1016/j.hrmr.2022.100899

Drydakis, N. (2022). Artificial Intelligence and Reduced SMEs' Business Risks. a Dynamic Capabilities Analysis during the COVID-19 Pandemic. *Information Systems Frontiers, 24,* 1223-1247. https://doi.org/10.1007/s10796-022-10249-6

Elia, G., Margherita, A., & Passiante, G. (2018). Digital Entrepreneurship Ecosystem: How Digital Technologies and Collective Intelligence Are Reshaping the Entrepreneurial Process. *Technological Forecasting and Social Change, 150,* Article ID: 119791.

https://doi.org/10.1016/j.techfore.2019.119791

Ferreira, C., Cardoso, C., Travassos, M., Paiva, M., Pestana, M., Lopes, J. M. et al. (2021). Disorders, Vulnerabilities and Resilience in the Supply Chain in Pandemic Times. *Logistics, 5,* Article 48. https://doi.org/10.3390/logistics5030048

Flora, M. (2022). *Supply Chain Performance: Key Metrics to Track & How to Improve It.* https://www.shipbob.com/blog/supply-chain-performance/

Fornell, C., & Larcker, D. F. (1981). Structural Equation Models with Unobservable Variables and Measurement Error: Algebra and Statistics. *Journal of Marketing Research, 18,* 382-388. https://doi.org/10.2307/3150980

Gama, F., & Magistretti, S. (2023). Artificial Intelligence in Innovation Management: A Review of Innovation Capabilities and a Taxonomy of ai Applications. *Journal of Product Innovation Management, 2023,* 1-36. https://doi.org/10.1111/jpim.12698

Gupta, H., Kumar, S., Kusi-Sarpong, S., Jabbour, C. J. C., & Agyemang, M. (2021). Enablers to Supply Chain Performance on the Basis of Digitization Technologies. *Industrial Management & Data Systems, 121,* 1915-1938. https://doi.org/10.1108/imds-07-2020-0421

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2017). *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)* (2nd ed.). Sage Publications Inc.

Hallikas, J., Immonen, M., & Brax, S. (2021). Digitalizing Procurement: The Impact of Data Analytics on Supply Chain Performance. *Supply Chain Management: An International Journal, 26,* 629-646. https://doi.org/10.1108/scm-05-2020-0201

Han, Y., Chong, W. K., & Li, D. (2020). A Systematic Literature Review of the Capabilities and Performance Metrics of Supply Chain Resilience. *International Journal of Production Research, 58,* 4541-4566. https://doi.org/10.1080/00207543.2020.1785034

Hohenstein, N., Feisel, E., Hartmann, E., & Giunipero, L. (2015). Research on the Phenomenon of Supply Chain Resilience. *International Journal of Physical Distribution & Logistics Management, 45,* 90-117. https://doi.org/10.1108/ijpdlm-05-2013-0128

Hove-Sibanda, P., & Pooe, R. I. D. (2018). Enhancing Supply Chain Performance through Supply Chain Practices. *Journal of Transport and Supply Chain Management, 12,* a400. https://doi.org/10.4102/jtscm.v12i0.400

Kochan, C. G., & Nowicki, D. R. (2018). Supply Chain Resilience: A Systematic Literature Review and Typological Framework. *International Journal of Physical Distribution & Logistics Management, 48,* 842-865. https://doi.org/10.1108/ijpdlm-02-2017-0099

Kopanaki, E., Karvela, P., & Georgopoulos, N. (2018). From Traditional Interorganisational Systems to Cloud-Based Solutions: The Impact on Supply Chain Flexibility. *Journal of Organizational Computing and Electronic Commerce, 28,* 334-353. https://doi.org/10.1080/10919392.2018.1517480

Kumar, P., Sharma, S. K., & Dutot, V. (2023). Artificial Intelligence (AI)-Enabled CRM Capability in Healthcare: The Impact on Service Innovation. *International Journal of Information Management, 69,* Article ID: 102598. https://doi.org/10.1016/j.ijinfomgt.2022.102598

Li, C. S., Wong, C. W. Y., Yang, C., Shang, K., & Lirn, T. (2020). Value of Supply Chain Resilience: Roles of Culture, Flexibility, and Integration. *International Journal of Physical Distribution & Logistics Management, 50,* 80-100. https://doi.org/10.1108/ijpdlm-02-2019-0041

Maestrini, V., Luzzini, D., Maccarrone, P., & Caniato, F. (2017). Supply Chain Performance Measurement Systems: A Systematic Review and Research Agenda. *International Journal of Production Economics, 183,* 299-315. https://doi.org/10.1016/j.ijpe.2016.11.005

Mikalef, P., & Gupta, M. (2021). Artificial Intelligence Capability: Conceptualization, Measurement Calibration, and Empirical Study on Its Impact on Organizational Creativity and Firm Performance. *Information & Management, 58,* Article ID: 103434. https://doi.org/10.1016/j.im.2021.103434

Mikalef, P., Fjørtoft, S. O., & Torvatn, H. Y. (2019). Developing an Artificial Intelligence Capability: A Theoretical Framework for Business Value. In W. Abramowicz, & R. Corchuelo (Eds.), *Business Information Systems Workshops* (pp. 409-416). Springer International Publishing. https://doi.org/10.1007/978-3-030-36691-9_34

Mishra, D., Gunasekaran, A., Papadopoulos, T., & Dubey, R. (2018). Supply Chain Performance Measures and Metrics: A Bibliometric Study. *Benchmarking: An International Journal, 25,* 932-967. https://doi.org/10.1108/bij-08-2017-0224

Modgil, S., Gupta, S., Stekelorum, R., & Laguir, I. (2022). AI Technologies and Their Impact on Supply Chain Resilience during Covid-19. *International Journal of Physical Distribution & Logistics Management, 52,* 130-149. https://doi.org/10.1108/ijpdlm-12-2020-0434

Nandi, M. L., Nandi, S., Moya, H., & Kaynak, H. (2020). Blockchain Technology-Enabled Supply Chain Systems and Supply Chain Performance: A Resource-Based View. *Supply Chain Management: An International Journal, 25,* 841-862. https://doi.org/10.1108/scm-12-2019-0444

Naz, S., Haider, S. A., Khan, S., Nisar, Q. A., & Tehseen, S. (2023). Augmenting Hotel Performance in Malaysia through Big Data Analytics Capability and Artificial Intelligence Capability. *Journal of Hospitality and Tourism Insights, 7,* 2055-2080. https://doi.org/10.1108/jhti-01-2023-0017

Ozdemir, D., Sharma, M., Dhir, A., & Daim, T. (2022). Supply Chain Resilience during the COVID-19 Pandemic. *Technology in Society, 68,* Article ID: 101847. https://doi.org/10.1016/j.techsoc.2021.101847

Özkanlısoy, Ö., & Bulutlar, F. (2023). Measuring Supply Chain Performance as SCOR V13.0-Based in Disruptive Technology Era: Scale Development and Validation. *Logistics, 7,* Article 65. https://doi.org/10.3390/logistics7030065

Pandey, J., Gupta, M., Behl, A., Pereira, V., Budhwar, P., Varma, A. et al. (2021). Technology-Enabled Knowledge Management for Community Healthcare Workers: The Effects of Knowledge Sharing and Knowledge Hiding. *Journal of Business Research, 135,* 787-799. https://doi.org/10.1016/j.jbusres.2021.07.001

Paschen, J., Kietzmann, J., & Kietzmann, T. C. (2019). Artificial Intelligence (AI) and Its Implications for Market Knowledge in B2B Marketing. *Journal of Business & Industrial Marketing, 34,* 1410-1419. https://doi.org/10.1108/jbim-10-2018-0295

Payyoli, A. G. (2022). *What Is Supply Chain Resilience?* https://www.linkedin.com/pulse/what-supply-chain-resilience-abdul-gafoor/

Pereira, V., & Mohiya, M. (2021). Share or Hide? Investigating Positive and Negative Employee Intentions and Organizational Support in the Context of Knowledge Sharing and Hiding. *Journal of Business Research, 129,* 368-381. https://doi.org/10.1016/j.jbusres.2021.03.011

Pires Ribeiro, J., & Barbosa-Povoa, A. (2018). Supply Chain Resilience: Definitions and Quantitative Modelling Approaches—A Literature Review. *Computers & Industrial Engineering, 115,* 109-122. https://doi.org/10.1016/j.cie.2017.11.006

Rahman, T., Paul, S. K., Shukla, N., Agarwal, R., & Taghikhah, F. (2022). Supply Chain Resilience Initiatives and Strategies: A Systematic Review. *Computers & Industrial Engineering, 170,* Article ID: 108317. https://doi.org/10.1016/j.cie.2022.108317

Rai, A., Constantinides, P., & Sarker, S. (2019). Editor's Comments: Next-Generation Digital Platforms: Toward Human-AI Hybrids. *Management Information Systems Quarterly,* *43,* iii-ix.

Rasool, F., Greco, M., & Grimaldi, M. (2022). Digital Supply Chain Performance Metrics: A Literature Review. *Measuring Business Excellence, 26,* 23-38. https://doi.org/10.1108/mbe-11-2020-0147

Reddy, K. J. M., Rao, A. N., & Krishnanand, L. (2019). A Review on Supply Chain Performance Measurement Systems. *Procedia Manufacturing, 30,* 40-47. https://doi.org/10.1016/j.promfg.2019.02.007

Salehi, H., & Burgueño, R. (2018). Emerging Artificial Intelligence Methods in Structural Engineering. *Engineering Structures, 171,* 170-189. https://doi.org/10.1016/j.engstruct.2018.05.084

Saunders, M., Lewis, P., & Thornhill, A. (2007). *Research Methods for Business Students* (4th ed.). Financial Times Prentice Hall.

Teece, D. J. (2007). Explicating Dynamic Capabilities: The Nature and Microfoundations of (Sustainable) Enterprise Performance. *Strategic Management Journal, 28,* 1319-1350. https://doi.org/10.1002/smj.640

Teece, D. J., Pisano, G., & Shuen, A. (1990). *Firm Capabilities, Resources, and the Concept of Strategy.* Economic Analysis and Policy Working Paper EAP, 38, University of California.

Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic Capabilities and Strategic Management. *Strategic Management Journal, 18,* 509-533. https://doi.org/10.1002/(sici)1097-0266(199708)18:7<509::aid-smj882>3.0.co;2-z

Teke, A., Pooe, R. I. D., & Munyayi, W. (2022). Evaluating the Supply Chain Performance of the Major Clothing Retail Companies in South Africa: A Supply Chain Index Approach. *Expert Journal of Marketing, 10,* 85-98. http://Marketing.ExpertJournals.com

Trisnawati, N., & Pujawan, I. N. (2021). Analysis of Supply Chain Performance Based on the Supply Chain Management Maturity Level in Manufacturing Industry. In *Proceedings of the International Conference on Industrial Engineering and Operations Management* (pp. 2152-2161). IEOM Society International. https://doi.org/10.46254/sa02.20210691

Tukamuhabwa, B., Stevenson, M., & Busby, J. (2017). Supply Chain Resilience in a Developing Country Context: A Case Study on the Interconnectedness of Threats, Strategies and Outcomes. *Supply Chain Management: An International Journal, 22,* 486-505. https://doi.org/10.1108/scm-02-2017-0059

Wamba, S. F., Queiroz, M. M., & Trinchera, L. (2020). Dynamics between Blockchain Adoption Determinants and Supply Chain Performance: An Empirical Investigation. *International Journal of Production Economics, 229,* Article ID: 107791. https://doi.org/10.1016/j.ijpe.2020.107791

Wamba-Taguimdje, S., Wamba, S. F., Kamdjoug, J. R. K., & Wanko, C. E. T. (2020). Impact of Artificial Intelligence on Firm Performance: Exploring the Mediating Effect of Process-Oriented Dynamic Capabilities. In R. Agrifoglio, R. Lamboglia, D. Mancini, & F. Ricciardi (Eds.), *Digital Business Transformation* (pp. 3-18). Springer International Publishing. https://doi.org/10.1007/978-3-030-47355-6_1

Wang, S., Sun, Z., & Chen, Y. (2023). Effects of Higher Education Institutes' Artificial Intelligence Capability on Students' Self-Efficacy, Creativity and Learning Performance. *Education and Information Technologies, 28,* 4919-4939. https://doi.org/10.1007/s10639-022-11338-4

Yamane, T. (1970). *Statistics: An Introductory Analysis* (2nd ed.). Harper & Row.

Yigit, A., & Kanbach, D. (2021). The Importance of Artificial Intelligence in Strategic

Management: A Systematic Literature Review. *International Journal of Strategic Management, 21,* 5-40. https://doi.org/10.18374/ijsm-21-1.1

Yuan, Y., & Beatrice, M. (2012). *Understanding the Supply Chain Resilience: A Dynamic Capabilities Approach.* https://mpra.ub.uni-muenchen.de/58124/

Yuhas, D. (2017). Doctors Have Trouble Diagnosing Alzheimer's. AI Doesn't. *NBC News.* https://www.nbcnews.com/mach/science/doctors-havetrouble-diagnosing-alzheimer-s-ai-doesn-t-ncna815561