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Evaluating the Economic Impacts of Artificial Intelligence Integration on Supply Chain Management; A Mediation Analysis through AI Capability

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Abstract

The objective of this study was to assess the correlation between Artificial Intelligence (AI) and the performance of Supply Chain Management (SCMP) while also investigating the mediating influence of AI Capability (AICAP). The hypotheses examined were as follows: H1, the beneficial influence of AI on SCMP; and H2, the mediating role of AICAP in the link between AI and SCMP. The research was underpinned by a positivist philosophy which supported in being able to carry out an objective analysis of AICAP's mediation between AI and SCMP. Regression analysis with a deductive way was used to investigate the relationship between independent and dependent variables. The ability to quantitatively analyze the data supported a comprehensive examination of hypotheses originally posited. Findings indicated that there is a strong positive association (r = 0.816) between AI and SCMP, with R2 of the variance in SCMP accounted by AI as 66.5%, therefore, continued support for H1 was established. Moreover, the mediating role of AICAP is significant (total effect = 0.8239 and mediation effect = 0.1862, implicating H2 as well. These results verify the importance of AI for SCMP improvement.

Keywords: *Artificial Intelligence, Supply Chain Management Performance, Artificial Intelligence Capability.*

Introduction

The rapidly evolving Artificial Intelligence (AI) technologies and increasing adoptions and deployments are raising much interest and huge investments by businesses in all business sectors. A few gaps still remain for the full potential that AI promises over traditional practice in supply chain management. Thus, the purpose of this study is two-fold: to highlight the impact of AI adoption on Supply Chain Management Performance (SCMP) but also to assess the intervening role played by Artificial Intelligence Capability (AICAP). Through this, the study also tries to give insights into opportunities and challenges related to the integration of AI advancement in supply chain processes. Outputs from the research will provide a basis for organizations to make informed decisions on leveraging AI opportunities for developing effective strategies towards increasing efficiency and effectiveness in supply chain management. Even though AI has not yet fully achieved the scale and depth of human intelligence, its efficiency in several tasks does have a very significant influence on organizations' performance and supply chain management. The research is primarily focused on considering the effects of AI on SCMP; hence, it fills a gap that is left open since no study of the same nature has been done before, mainly in the Arab world. In addition, the paper has the following secondary objectives:

- Understanding the concepts of AI, SCMP, and AICAP from both theoretical and empirical standpoints.
- Investigating the function of AICAP as a moderator in the relationship between AI and SCMP, specifically its impact on the extent to which AI influences SCMP.
- Exploring the opportunities and benefits of AI-powered transformation initiatives within organizations.
- Examining the influence of AICAP on organizational improvement and SCMP enhancement.

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Literature Review

Artificial Intelligence (AI)

Artificial Intelligence (AI) involves the empowerment of computer programs with the capabilities to mimic human intelligence, enabling them to make decisions and execute complex tasks more efficiently for businesses. Lu (2019) highlights the significance of AI-specific devices in linking, analyzing, and applying data, noting that their transformative potential for corporate operations is evident in daily use, such as with Amazon's Alexa. Despite its ubiquity, the definition of AI remains elusive within the scientific community, with interpretations ranging from Buchanan and Shortliffe's (1985) symbol-based problem solving to Rich's (1983) view of AI performing human-like tasks—a notion that continually evolves as AI surpasses human capabilities. Other perspectives, such as those of Staugaard (1987) and Charniak and McDermott (1985), see AI as an imitation of human thought or the study of natural cognitive processes. Saleh et al. (2019) extend this to encompass the level of intelligence in natural beings. The history of AI reflects significant advancements, from ancient automata to modern developments like Google Transformer and OpenAI GPT-2, illustrating its evolving functionality in the contemporary era (Luitse & Denkena, 2021).

Artificial Intelligence Capability (AIC)

Artificial Intelligence (AI) comprises several critical technologies such as expert systems, fuzzy logic, artificial neural networks (ANNs), machine learning (ML), deep learning, natural language processing (NLP), reinforcement learning, computer vision, and robotics, all aimed at replicating human intelligence through computers. Such technologies make AI effective and efficient in its applications, ranging from advanced data analysis, prediction, and automation in different scopes. One of the AI standouts is machine learning. This type of AI enables systems to autonomously learn from data without requiring explicit programming for the learning process. Machine learning is a method of statistical methods that allows models to train on data so that, over time, they can change and improve predictive accuracy. Machine learning has applications in domains ranging from anti-malware to dynamic forecasting models that can be used for effective sifting of complex, uncertain scenarios (Sarker, 2021). Natural Language Processing (NLP) is the nucleus of AI; it includes intelligence and computational linguistics, which enables machines to understand and interpret human languages. Through NLP, an AI system can process unstructured text, allowing it to translate unstructured text into actions, for example, by recognizing a speech command, analyzing text for topic extraction, and translation from one language to another. NLP has brought about the development of intelligent search engines, responsive chatbots, and assistive technologies for the visually challenged human being (Sadiku, Zhou, and Musa, 2018). Expert systems aim to imitate the powers of human expertise in decision-making, using the knowledge and reasoning capabilities that a human being possesses. These systems evaluate data using rule-based inference and offer expert advice on complex problems, representing a significant application of AI in business and other domains (Matthew et al., 2020).

Artificial Neural Networks (ANNs), inspired by the human nervous system, are designed to recognize patterns and categorize information through a structure of interconnected nodes mimicking neurons. They excel in areas such as medical diagnostics and risk assessment, demonstrating the ability to model complex, nonlinear relationships rapidly (Matthew et al., 2020).

Reinforcement learning trains systems by trial-and-error, optimizing behaviors through rewards. It is, however, a topic of very active research, showing much promise in robotics (Kormushev, Calinon, and Caldwell, 2013). On the other hand, fuzzy logic deals with uncertain decision-making, and deep learning and data mining grope with solving intricate problems, along with digging out patterns from huge data (Jiang, 2017). The increase in AI-based solutions in organizations will change the focus of the research from broad explorations to practical applications and operational support of leveraging AI for organizational strategic objectives (Mikalef & Gupta, 2021; Bytniewski et al., 2020; Schmidt et al., 2020). All these efforts are approached from the perspective of integration with technology and nontechnology, such as employee skills and analytics, to reinforce strategic value (Patrick & Manjul, 2021; Wamba-Taguimdje et al., 2020; Schmidt et al., 2017). AI's support capabilities take tangible assets, human expertise, and intangible

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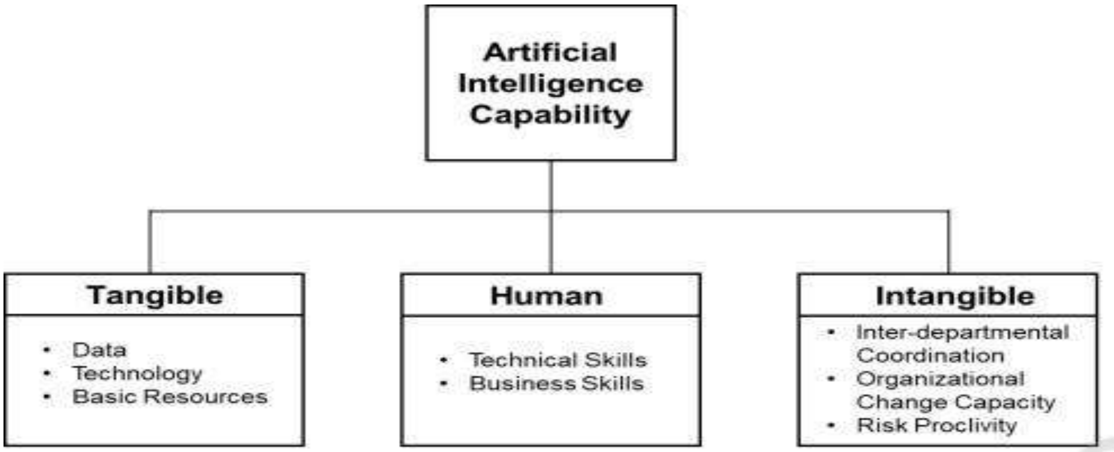
resources required for strategic benefits (Pandey et al., 2022).

Figure1. Artificial Intelligence Capability



Source: Patrick and Manjul (2021, p.4)

SCM Practices

Supply Chain Management (SCM) practices encompass a range of activities aimed at enhancing supply chain efficiency, as outlined by various scholars. Donlon (1996) highlights modern SCM practices such as outsourcing and the use of information technology, while Tan et al. focus on aspects like quality and customer relations, identifying six key facets of SCM practice, including integration and customer service management. The academic consensus underlines that effective SCM practices are vital for enhancing organizational performance, focusing on five main dimensions: strategic supplier partnerships, customer relationships, levels and quality of information sharing, and postponement strategies.

These aspects comprehensively cover both the supply and demand sides of the supply chain, along with information flow and internal processes. A strategic partnership with suppliers, founded on shared risks and benefits beyond just cost considerations, is crucial for a successful supply chain. This approach prioritizes long-term collaboration and mutual problem-solving, which is essential for adapting to dynamic market conditions (Oliver and Delbridge, 2002; Sachdeva et al., 2021; Gunasekaran et al., 2001; Sambasivan et al., 2013; Talib et al., 2011; Malhotra and Mackelprang, 2012; Islami, 2023).It is a long-term relationship that works in technology, product development, and market development and provides strategic and operational performance improvements in a mutual win-win manner. This will deal with strategic supplier partnerships, technology, product development, and market expansions (Stuart, 1997; Gunasekaran, Patel, and Tirtiroglu,2001). Early supplier involvement in the design of products offers huge improvements in cost efficiency and component selection (Yoshino & Rangan, 1995). Customer relationship management (CRM) is the process of technology and human integration to create or develop a bond of rapport between customers with the aim of developing business performance and loyalty through data management and complaint resolution (Das, S., Mishra, M., & Mohanty, P. K., 2018). Information sharing, therefore, is indispensable in supply chain management (SCM) for improved visibility and coordination between sales, production, and logistics through the use of technologies such as electronic data interchange, which consequently leads to cost savings and inventory efficiency (Lee and Whang, 2000; Frohlich, 2002; Handfield & Nichols, 1999; Handfield & Bechtel, 2002; Pandey et al., 2010). It eventually facilitates good information exchange in a high-quality form, which supports improved strategic, tactical, and operational decision-making while supporting supply chain performance and market responsiveness (Rabren, 2010; Ramayah and Omar, 2010; Li et al., 2006; Miller, 2005; Raghunathan, 1999). In SCM, the postponement concept helps to mitigate the risks of product differentiation and balance the speculation strategies between inventory optimization and response to market demands. Alderson (2006), Bucklin (1965), Shapiro (1984),

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Pagh and Cooper (1998), and Ernst and Kamrad (2000) indicated that postponement, in this case, helps to mitigate these risks.

AI in Strengthening Supply Chain Management

According to a McKinsey survey, 2022, the transformative impacts of AI on supply chain operations are underlined. It further implies that companies can reduce the logistic cost by 15% with improved demand forecasting and inventory management, which also helps in increasing the inventory efficiency by 35% and service level by 65%. More than 150 CEOs, or around 70%, acknowledged that substantial ROI with AI is identifiable despite the huge cost of the initial investment (Cohen & Tang, 2024). Artificial intelligence helps in increasing the visibility and resilience of supply chains in that it analyzes various data that will help in coming up with a premonitory strategy on the way to handle market fluctuations (Ajami, 2023). It also supports improved operational efficiency, quality control, and promotion of innovation in all sectors. However, artificial intelligence comes with risks that require full regulation for responsible use and integrity of the digital ecosystem (Ajami, 2023).

Conceptual Framework

As companies incorporate AI technologies into their operations, it becomes crucial to assess their impact on Supply Chain Management Performance (SCMP). This research aims to bridge this knowledge gap by addressing the following key research question and sub-questions:

The primary research question is:

- *"What is the effect of Artificial Intelligence on Supply Chain Management Performance?"*

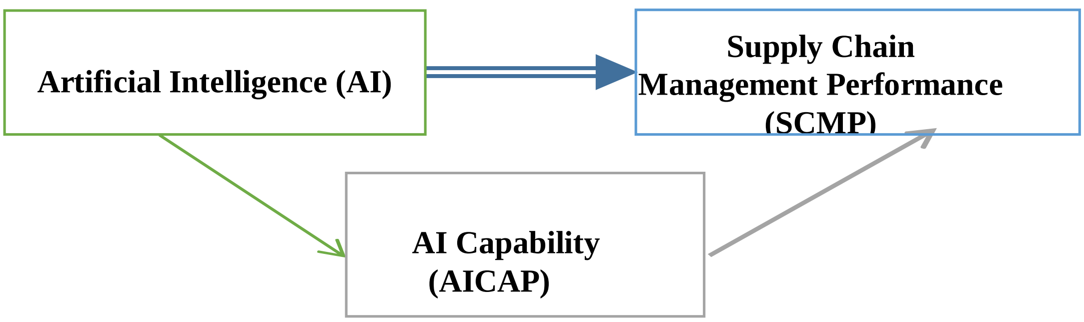
Additionally, this study will explore two supplementary research questions, as stated below:

- R.Q1. How does AI capability affect performance improvement at both organizational and process levels?
- R.Q2. What are the organizational economic benefits of AI-driven transformation initiatives?

The hypotheses formulated for this study are as follows:

- Hypothesis 1: There is a significant positive correlation between AI and SCMP.
- Hypothesis 2: AI capability acts as a mediating factor in the relationship between AI and Supply Chain Management Performance.

Figure 2. Conceptual Framework



Source: Prepared by the researcher

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Research Methodology

This research adopts a deductive methodology, utilizing theories and generalizations to guide the collection of primary data through questionnaires. Emphasizing a quantitative approach, the study is anchored in positivism, relying on scientific literature related to AI, AICAP, and SCMP for its framework. Data will be analyzed with SPSS, and questionnaires will be shared on social media to target employees in private SMEs in Lebanon and the United Arab Emirates. These employees, engaged in firms utilizing AI for business processes, represent the study's core demographic, aiming to assess AI's impact on SCM and the intermediary role of AI capability. The study employs a structured questionnaire to gather data for statistical analysis to probe the dynamics between AI, AI capability, and SCM. The survey, facilitated via Google Forms for efficiency and cost-effectiveness, targets employees knowledgeable about the study's variables in Lebanon, France, Norway, and the UAE. A total of 60 responses were collected through purposive sampling, analyzed in SPSS version 29 to investigate the hypothesized relationships among the variables using descriptive statistics, simple linear regression, and the PROCESS macro by Hayes (2013) for mediation analysis.

Results and Discussion Findings

The researcher aims at ensuring several analytical approaches that would enhance the identification of the impact of AI on SCM, particularly in the Arab world, and have mostly researched AI capabilities as a moderator. These help in answering questions in research and testing hypotheses based on questions related to AI, SCM, and AI competence.

Descriptive Statistics

Table 1. Age Descriptive Statistics

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	18-25 y	4	6.6	6.6	6.6
	26-35 y	23	37.7	37.7	44.3
	36-45 y	11	18.0	18.0	62.3
	46-60 y	21	34.4	34.4	96.7
	above 60 y	2	3.3	3.3	100.0
	Total	61	100.0	100.0	

The age factor in this study shows that the highest number of participants' age was between 26-35 and 40-60 years old, in which 37.7% out of 61 respondents was between26-35 and 34.4% was between 40-60 years old. While the lowest number of participants was between 18-25 years and above 6o years old in which 6.6% out of 61 respondents was between 18-25 years old and only 3.3% out of 61% out of 61 respondents was above 60 years old.

Table 2. Profession Descriptive Statistics

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Employee	30	49.2	49.2	49.2
	Supervisor	11	18.0	18.0	67.2
	Manager	20	32.8	32.8	100.0
	Total	61	100.0	100.0	

The participant's profession result in this study shows that 49.2% out of 61 respondents were employees, 18% were supervisors while 32.8% out of 61 respondents were managers.

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Hypotheses Testing

H1 analysis: Pearson Correlation and Simple Linear Regression

Table 3. Correlations

Correlations

		SCM	ArtifInt
SCM	Pearson Correlation	1	.816**
	Sig. (2-tailed)		.000
	N	61	61
ArtifInt	Pearson Correlation	.816**	1
	Sig. (2-tailed)	.000	
	N	61	61

The regression analysis was used in this study to determine the effect of each of the aforementioned hypotheses on the dependent variable. Regression is a statistical technique that aids in analyzing the relationship among the dependent and the independent variable. In our study the independent variable is artificial intelligence (AI), while the dependent variable is Supply Chain Management (SCM).

Table 4. Simple Linear Regression

Variables Entered/Removed [a]

Model	Variables Entered	Variables Removed	Method
1	AI[b]	.	Enter
a. Dependent Variable: SCM			
b. All requested variables entered.			

The R and R2 values are provided in this table. The R value (the "R" Column) displays the simple correlation and is 0.816, indicating a high degree of relation. The R2 value (column "R Square") reflects how much of the entire variance in the dependent variable, SCM, can be explained by the independent variable AI. In this scenario, the model accounts for 66.5% of the variance in supply chain management in terms of artificial intelligence.

Table 5. Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.816[a]	.665	.660	.46561	.665	117.285	1	59	.000
a. Predictors: (Constant), AI									
b. Dependent Variable: SCM									

The table below shows that the regression model accurately predicts the dependent variable. This reflects the statistical significance of the regression model used. In this case, p=0.000, which is less than 0.01, shows that the regression model is statistically significant overall.

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Table 6. ANOVA

Model		Sum of Squares	Df	Mean Square	F	Sig.
1	Regression	25.427	1	25.427	117.285	.000[b]
	Residual	12.791	59	.217		
	Total	38.218	60			
a. Dependent Variable: BPM						
b. Predictors: (Constant), AI						

In the table below, focus on the Sig. value, which should be less than the tolerable value of 0.01, and the B coefficient, which indicates the slope of the regression line, from which we can derive the equation y = ax + b, which clarifies how the dependent variable (y) changes as a result of a change in the independent variable (x).

*Supply Chain Management = 0.733 + 0.824 * (AI)*

Table 7. Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.733	.285		2.570	.013
	AI	.824	.076	.816	10.830	.000
a. Dependent Variable: BPM						

H2: Mediation Analysis (macro-PROCESS of Hayes (2019))

The analysis investigated the impact of AI on Supply Chain Management Performance (SCM) with AI Capability (AICAP) serving as a mediator, using the PROCESS procedure for SPSS Version 4.2. The study included 61 participants.

The first model, focusing on AICAP as the outcome variable, revealed a strong positive relationship between AI and AICAP. The results indicated a significant positive effect of AI on AICAP (b = 0.7141, t = 8.4657, p < 0.0001), with a high degree of explained variance (R-squared = 0.5485).

The second model, which included AI and AICAP as predictors of the outcome variable Process, also demonstrated robust findings. AI had a significant impact on Process (b = 0.6377, t = 5.8336, p < 0.0001), and AICAP showed a significant effect (b = 0.2608, t = 2.3004, p = 0.0250). This model explained a substantial proportion of the variance in Process (R-squared = 0.6933).

The strong evidence of the strong impact of AI was further supported by the total effect model on SCM as the outcome variable, which also showed a strong direct effect on SCM (b = 0.8239, t = 10.8298, p < 0.0001) and explained a considerably high proportion of the variance (R-squared = 0.6653). As well, the findings on the decomposition of total, direct, and indirect effects demonstrate that the total effect of AI on SCM is not only significant but also considerable in magnitude. The direct effect from AI to SCM is significant and independent of the mediational role of AICAP. The significant indirect effect mediated by AICAP confirms the mediating role of AICAP with its findings but further concludes that there is a strong mediating role of AICAP in the relationship of AI and SCM. That is, a direct influence is made on SCM through AI, and performance is influenced by AI through AICAP's indirect influence. This model helps us better understand the mechanisms by which AI enhances SCM performance. These results establish that AI capability plays a very critical role in the optimization of SCM processes. The results further show that AI-driven solutions must be embedded into supply chain strategies.

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Evaluation of Findings

The integration of Artificial Intelligence (AI) within Supply Chain Management (SCM) has garnered significant scholarly attention, particularly focusing on the interplay between AI, AI capabilities, and their influence on SCM. This analysis highlights the critical role of AI capabilities as a bridge between AI technology and SCM enhancements. Initial findings, underscored by a Cronbach alpha reliability test result exceeding 0.7 for all questionnaire items, affirm the reliability and validity of the research instruments. Furthermore, a positive correlation was established between AI implementation and SCM improvements, with significant outcomes such as enhanced customer satisfaction, reduced costs, and increased efficiency, aligning with broader academic findings that advocate AI as a catalyst for process innovation.

The study also sought to delve into the mediation of AI capabilities in the AI-SCM relationship, factored in again through linear regression analysis. This, therefore, signifies that the level of positive influence AI will have on SCM will greatly depend on the ability of the firm to effectively manage these AI technologies. Therefore, companies investing in their AI capabilities are more likely to leverage AI's full potentials in streamlining their SCM processes. The findings of this research, therefore, partially agree with the existing literature such as studies done on AI in marketing through social media for SMEs in Saudi Arabia, AI in the firm's performance, and the way e-commerce adoption inter-links with the performance of SMEs in Sri Lanka through the mediational role of AI. This underscores the transformational potential of AI in improving business processes. Towards this direction, companies should develop their AI competencies in case they want to benefit from the use of AI in SCM. This paper rationalizes the use of AI in SCM by demonstrating its utility and underscoring core importance for the current time of developing AI capabilities.

Conclusion and Recommendations

Although the growing field of Artificial Intelligence (AI) has propelled what is considered a gold rush in business circles in terms of interest and investment, there exists a serious gap between developing a comprehension of how the traditionally practiced AI impact SCM and the role AI capabilities play in mediating the traditionally practiced impact. Yet, AI performs well in specialized tasks, which can have a considerable effect on businesses and SCM. The goal of the present study was to fill the gap in research on the role of AI in SCM that has been evident in the Arab region.

Significant findings to the level of AI and SCM improvements are showing a strong positive correlation ($r = 0.816$), which meant that there is a large effect of AI towards enhancing supply chain efficiency and effectiveness. Further, validation of the research instruments was appreciated through a Cronbach's alpha score of 0.974, and the regression analysis indicated that AI accounts for 66.5% of the variance in SCM, underpinning the pivotal role of AI for SCM optimization.

This study demonstrates how AI can transform Supply Chain Management (SCM) from an economic perspective through predictive analytics, enhanced decision-making processes, and automation, ultimately leading to increased productivity, cost reductions, and improved customer engagement. The findings highlight the necessity for businesses to invest in developing AI capabilities to fully realize the benefits AI offers to SCM.

It is recommended that businesses invest in technologies such as AI to enhance SCM capabilities, develop internal AI competencies, and formulate an AI integration strategy. Future research should target larger sample sizes for broader generalizability, explore specific AI applications within SCM in greater detail, and continuously monitor AI advancements to keep pace with this rapidly evolving field.

References

Alderson, W. (2006). Marketing efficiency and the principle of postponement. In A twenty-first century guide to Aldersonian marketing thought . Boston, MA: Springer US.pp:109-113.

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DOI: https://doi.org/10.62754/joe.v3i7.4226
Annamalah, S., Paraman, P., Ahmed, S., Dass, R., Sentosa, I., Pertheban, T. R & Singh, P. (2023). The role of open innovation and a normalizing mechanism of social capital in the tourism industry. Journal of Open Innovation: Technology, Market, and Complexity, 9(2), 100056. https://doi.org/10.1016/j.joitmc.2023.100056.

Barney, J. (1991) Firm Resources and Sustained Competitive Advantage. Journal of Management, 17. Pp: 99-120.

Bharadwaj, A. S. (2000). A Resource-Based Perspective on Information Technology Capability and Firm Performance: An Empirical Investigation. MIS Quarterly 24(1). pp: 169–196. http://dx.doi.org/10.2307/3250983

Buchanan, B. G.: 1985, 'Steps toward Mechanizing Discovery', in K. F. Schaffner (ed.), Logic of Discovery and Diagnosis in Medicine, chapter 4, University of California Press, Berkeley, CA, pp. 94–114.

Bucklin, L. P., (1965), Postponement, speculation and the structure of distribution channels. Journal of Marketing Research 2. pp: 26–31.

Bytniewski, A., Matouk, K., Chojnacka-Komorowska, A., Hernes, M., Zawadzki, A., & Kozina, A. (2020, March). The functionalities of cognitive technology in management control system. In Asian Conference on Intelligent Information and Database Systems. Cham: Springer International Publishing. pp:230-240. https://doi.org/10.1007/978-3-030-42058-1_19

Charinak, E., & McDermott, D. V. (1985). Introduction to Artificial Intelligence. MA: Addison-Wesley.

Chintalapati, S., & Pandey, S. K. (2022). Artificial intelligence in marketing: A systematic literature review. International Journal of Market Research, 64(1), 38-68. https://doi.org/10.1177/14707853211018428

Chui, M., & Malhotra, S. (2018). AI adoption advances, but foundational barriers remain. Mckinsey and company.

Cohen M. and Tang C, (2024) The Role of AI in Developing Resilient Supply Chains, Georgetown Journal of International Affairs, Walsh School of Foreign Service.

Daugherty, P. J., Ellinger, A. E., & Rogers, D. S. (1995). Information accessibility: Customer responsiveness and enhanced performance. International Journal of Physical Distribution & Logistics Management, 25(1). pp: 4-17. http://dx.doi.org/10.1108/09600039510080117

Davenport, T. H., & Ronanki, R. (2018). Artificial intelligence for the real world. Harvard business review, 96(1). pp: 108-116.

Donlon, J. P. (1996). Maximizing value in the supply chain. Chief Executive, 117(1). pp:54-63.

Gunasekaran, A., Patel, C., & Tirtiroglu, E. (2001). Performance measures and metrics in a supply chain environment. International journal of operations & production Management, 21(1/2). pp: 71-87. https://doi.org/10.1108/01443570110358468

Dyche, J. (2002). The CRM handbook: A business guide to customer relationship management. Addison-Wesley Professional.

Eisman, A. (2008). Achieving a high-performance supply chain: Sharing information with partners. Business Intelligence Journal, 13(2), 29. https://doi.org/10.1145/3460537.3460558

Ernst, R. and Kamrad, B., (2000), Evaluation of supply chain structures through modularization and postponement. European Journal of Operational Research, 124. pp:495–510.

Forslund H, Jonsson P (2007). The impact of forecast information quality on supply chain performance. International journal of operations & production management, 27(1). pp 90-107. https://doi.org/10.1108/01443570710714556

Fountaine, T., McCarthy, B., & Saleh, T. (2019). Building the AI-powered organization. Harvard Business Review, 97(4). pp: 62-73.

Frohlich, M.T. (2002), E-integration in the supply chain: barriers and performance, Decision Sciences, vol. 33, no. 4. pp: 537-56.

Gunasekaran, A., Patel, C., & Tirtiroglu, E. (2001). Performance Measures and Metrics in a Supply Chain Environment. International Journal of Operations and Production Management, 21. pp: 71-87. https://doi.org/10.1108/01443570110358468

Gustin CM, Daugherty PJ, Stank TP (1995). The effects of information availability on logistics integration. Journal of business Logistics, 16(1). pp: 1-21

Handfield, R.B. and Bechtel, C. (2002), The role of trust and relationship structure in improving supply chain responsiveness, Industrial Marketing Management, vol. 31, no. 4. pp: 367-82.

Handfield, R.B. and Nichols, L.E. (1999), Introduction to Supply Chain Management, Prentice-Hall, New Delhi.

Helm, J. M., Swiergosz, A. M., Haeberle, H. S., Karnuta, J. M., Schaffer, J. L., Krebs, V. E., Spitzer, A. I., & Ramkumar, P. N. (2020). Machine Learning and Artificial Intelligence: Definitions, Applications, and Future Directions. Current reviews in musculoskeletal medicine, 13(1). pp: 69–76. https://doi.org/10.1007/s12178-020-09600-8

Huang GQ, Lau JSK, Mak KL (2003). The impacts of sharing production information on supply dynamics: a review of the literature. International journal of production research, 41(7). pp: 1483-1517.

Islami, X. (2023), Lean manufacturing and firms' financial performance: the role of strategic supplier partnership and information sharing, Benchmarking: An International Journal, vol. 30, no. 9. pp : 2809-2831. http://dx.doi.org/10.18845/te.v17i3.6846

Jiang, F., Jiang, Y., Zhi, H., Dong, Y., Li, H., Ma, S., & Wang, Y. (2017). Artificial intelligence in healthcare: past, present and future. Stroke and vascular neurology, 2(4). https://doi.org/10.1136/svn-2017-000101

Kormushev, Petar & Calinon, Sylvain & Caldwell, Darwin. (2013). Reinforcement Learning in Robotics: Applications and Real-World Challenges. Robotics 2.pp: 122-148. https://doi.org/10.3390/robotics2030122.

Lee HL, Padmanabhan V, Whang S (1997a). The bullwhip effect in supply chains. Sloan management review, 38(3). pp: 93-102.

Lee HL, Padmanabhan V, Whang S (1997b). Information distortion in a supply chain: the bullwhip effect. Managemnet Science, 43(4). pp: 546-558.

Lee, G.L. and Oakes, I.K. (1996), "Templates for change with supply chain rationalization", International Journal of Operations & Production Management, vol. 16, no. 2. pp: 197-209.

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DOI: https://doi.org/10.62754/joe.v3i7.4226
Lee, H.L. and Whang, S. (2000), "Information sharing in a supply chain", International Journal of Technology Management, vol. 20, no. 3/4. pp: 373-87.

Li S, Ragu-Nathan B, Ragu-Nathan TS, Rao SS (2006). The impact of supply chain management practices on competitive advantage and organizational performance. Omega 34. pp:107- 124.

Lu, Y. (2019). Artificial intelligence: a survey on evolution, models, applications and future trends. Journal of Management Analytics, 6(1). pp: 1-29. https://doi.org/10.1080/23270012.2019.1570365

Luitse, D., & Denkena, W. (2021). The great Transformer: Examining the role of large language models in the political economy of AI. Big Data & Society, 8(2).

Malhotra, M.K. and Mackelprang, A.W. (2012), "Are internal manufacturing and external supply chain flexibilities complementary capabilities?", Journal of Operations Management,vol. 30, no. 3. pp: 180-200. https://doi.org/10.1016/j.ijpe.2019.03.026

Manoliu D., Ungureanu n., (2023), Closing the Gap between Relationship Marketing, Customer Relationship Management and Customer Complaint Management, Scientific Bulletin, Serie C, Fascicle: Mechanics, Tribology, Machine Manufacturing Technology (37). pp: 28-33

Melville, N., Gurbaxani, V., & Kraemer, K. (2007). The productivity impact of information technology across competitive regimes: The role of industry concentration and dynamism. Decision support systems, 43(1). pp: 229-242. https://doi.org/10.1016/j.dss.2006.09.009

Mikalef, Patrick & Gupta, Manjul. (2021). Artificial Intelligence Capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance. Information & Management. 58(3). https://doi.org/10.1016/j.im.2021.103434

Miller, H. (2005). Information quality and market share in electronic commerce. Journal of Services Marketing, 19(2). pp: 93-102.

Oliver, N. and Delbridge, R. (2002), The characteristics of high performing supply chains, International Journal of Technology Management, vol. 23, nos 1/2/3. pp: 60-73.

Omar, R., Ramayah, T., Lo, M. C., Sang, T. Y., & Siron, R. (2010). Information sharing, information quality and usage of information technology (IT) tools in Malaysian organizations. African journal of business management, 4(12), 2486.

Orlitzky, M., Schmidt, F. L., & Rynes, S. L. (2003). Corporate social and financial performance: A meta-analysis. Organization studies, 24(3). pp: 403-441. https://doi.org/10.1177/0170840603024003910

Pagh, J. D. and Cooper, M. C., (1998), Supply chain postponement and speculation strategies: how to choose the right strategy. Journal of Business Logistics, 19. pp:13–33.

Panahifar, F., Byrne, P.J., Salam, M.A. and Heavey, C. (2018), "Supply chain collaboration and firm's performance: the critical role of information sharing and trust", Journal of Enterprise Information Management, vol. 31, no. 3. pp:358-379. https://doi.org/10.1108/JEIM-08-2017-0114

Pandey, V. C., Garg, S. K., & Shankar, R. (2010). Impact of information sharing on competitive strength of indian manufacturing enterprises: An empirical study. Business Process Management Journal, 16(2). pp: 226-243. https://doi.org/10.1108/14637151011035570

Papadopoulos, T., Gunasekaran, A., Dubey, R., Altay, N., Childe, S.J. and Fosso-Wamba, S. (2017), "The role of big data in explaining disaster resilience in supply chains for sustainability", Journal of Cleaner Production, vol. 142, no. 2. pp: 1108-1118

Rabren J (2010). Technology, Integration and Data Drive Supply Chain Visibility. Material Handling Management, Retrieved Business Source Complete database, 65(3): 42.

Raghunathan S (1999). Impact of information quality and decision-maker quality on decision quality: a theoretical model and simulation analysis. Decision Support System, 26. pp: 275-286. https://doi.org/10.1016/S0167-9236(99)00060-3

Ramayah T, Omar R (2010). Information Exchange and Supply Chain Performance International journal of information technology & decision making, 9(1). pp: 35-52. https://doi.org/10.1142/S0219622010003658

Ransbotham, S., Kiron, D., Gerbert, P., & Reeves, M. (2017). Reshaping business with artificial intelligence: Closing the gap between ambition and action. MIT sloan management review, 59(1).

Ravichandran, T. & Lertwongsatien, Chalermsak. (2005). Effect of Information Systems Resources and Capabilities on Firm Performance: A Resource-Based Perspective, 21. pp: 237-276. https://doi.org/10.1080/07421222.2005.11045820

Redman TC (1998). The impact of poor data quality on the typical enterprise. Association for Computing Machinery, Communications of the ACM, 41(2). pp: 79-82.

Riad A. Ajami & Homa A. Karimi (2023) Artificial Intelligence: Opportunities and Challenges, Journal of Asia-Pacific Business, 24:2. pp: 73-75. https://doi.org/10.1080/10599231.2023.2210239

Rich, E. (1985). Artificial intelligence and the humanities. Computers and the Humanities, 19(2). pp: 117-122. https://doi.org/10.1007/BF02259633

Rossin D (2007). An exploratory analysis of information quality in supply chains: efficient and responsive models. Journal of Global Business Issues, 1(2), pp: 151- 158.

Sachdeva, N., Shrivastava, A.K. and Chauhan, A. (2021), Modeling supplier selection in the era of Industry 4.0, Benchmarking: An International Journal, vol. 28, no. 5. pp: 1809-1836.

Sadiku, Matthew & Ashaolu, Tolulope Joshua & Ajayi-Majebi, Abayomi & Musa, Sarhan. (2021). Artificial Intelligence in Education. International Journal Of Scientific Advances (2).

Sambasivan, M., Siew-Phaik, L., Abidin Mohamed, Z. and Choy Leong, Y. (2013), "Factors influencing strategic alliance outcomes in a manufacturing supply chain: role of alliance motives, interdependence, asset specificity and relational capital", International Journal of Production Economics, vol. 141, no. 1. pp: 339-351

Sarker, I. H. (2021). Machine learning: Algorithms, real-world applications and research directions. SN computer science, 2(3), 160. https://doi.org/10.1007/s42979-021-00592-x

Volume: 3, No: 7, pp. 578 – 588
ISSN: 2752-6798 (Print) | ISSN 2752-6801 (Online)
https://ecohumanism.co.uk/joe/ecohumanism
DOI: https://doi.org/10.62754/joe.v3i7.4226
Seddon, Peter. (2014). Implications for strategic IS research of the resource-based theory of the firm: A reflection. The Journal of Strategic Information Systems. 23. https://doi.org/10.1016/j.jsis.2014.11.001
Shapiro, R. D., (1984), Get leverage from logistics. Harvard Business Review, 62. pp:119–126.
Singh J (1996). The importance of information flow within the supply chain. Logistics Information Management, 9(4). pp: 28-30.
Staugaard Jr, A. C. (1987). Robotics and AI: an introduction to applied machine intelligence. Prentice-Hall, Inc.
Stuart, F. I. (1997). Supply-Chain Strategy: Organizational Influence through Supplier Alliances. British Academy of Management, 8. pp: 223-236.
Sutton, R. S., & Barto, A. G. (2018). Reinforcement learning: An introduction (2nd ed.). The MIT Press.
Talib, F., Rahman, Z. and Qureshi, M.N. (2011), A study of total quality management and supply chain management practices, International Journal of Productivity and Performance Management, vol. 60, no. 3. pp: 268-288. https://doi.org/10.1108/17410401111111998
Tan, K. C., Lyman, S. B., & Wisner, J. D. (2002). Supply Chain Management: A Strategic Perspective. International Journal of Operations and Production Management, 22. pp: 614-631. http://dx.doi.org/10.1108/01443570210427659
Wamba-Taguimdje, S. L., Fosso Wamba, S., Kala Kamdjoug, J. R., & Tchatchouang Wanko, C. E. (2020). Influence of artificial intelligence (AI) on firm performance: the business value of AI-based transformation projects. Business Process Management Journal, 26(7). pp: 1893-1924. https://doi.org/10.1108/BPMJ-10-2019-0411
Waterman, D. A. (1985). A guide to expert systems. Addison-Wesley Longman Publishing Co., Inc.
Yang, B. and Burns, N. D., (2002), Postponement in new product introduction. In Proceedings of the 10th International Manufacturing Conference in China, Xiamen, P. R. China.
Yang, Biao & Burns, Neil. (2003). Implications of postponement for the supply chain. International Journal of Production Research. 41. pp: 2075-2090. https://doi.org/10.1080/00207544031000077284
Yoshino, M., & Rangan, S. (1995). Strategic Alliances: An Entrepreneurial Approach to Globalization. Harvard Business School Press
Yu Z, Yan H, Cheng TCE (2001). Benefits of information sharing with supply chain partnerships. Industrial management & Data systems, 101(3). pp: 114- 121. https://doi.org/10.1108/02635570110386625
Zhang C, Tan GW, Robb DJ, Zheng X (2006). Sharing shipment quantity information in the supply chain. Omega, 34. pp: 427-438. https://doi.org/10.1016/j.omega.2004.12.005.