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EFFECTS OF ARTIFICIAL INTELLIGENCE ON SUPPLY CHAIN OPERATIONAL PERFORMANCE: ROLE OF OPERATIONS ADAPTIVE CAPABILITIES AND AMBIDEXTERITY INNOVATION

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Research Paper

Abstract: *Research aimed to test the influence of artificial intelligence-based factors on supply chain operations performance. The study also tested the mediating effect of operations adaptive capabilities and operations ambidexterity. For this purpose, collected data from 390 employees of SMEs in Saudi Arabia employing a convenient sampling technique. The survey based study used a cross-sectional research design and quantitative approach. The structural model results show that AI-based risk management, AI-based innovations, and generative AI have a positive and significant impact on supply chain performance. On the other hand, indirect mediating effect results also show that operations adaptive capabilities and operations ambidexterity innovation positively and significantly mediated among all AI-based indicators and supply chain performance of SMEs in Saudi Arabia. The study on the findings of AI-based factors to improve supply chain operations performance contributed empirical literature in the context of Saudi Arabian SMEs. Furthermore, study also highlighted the mediating effect of operations adaptive capabilities and operations ambidexterity innovation in strengthening the relationship between AI indicators and supply chain operations performance. These findings provide valuable insights for SMEs seeking to leverage AI technologies to improve supply chain operational performance.*

Keywords: *AI-based risk management, Supply chain operations performance, Adaptive capabilities, SMEs, Saudi Arabia.*

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1. Introduction

Supply chain operations become an integral component of the sustainability and long-term survival of any organization (Saragih et al., 2020). Improvement in supply chain operations not only increased the efficiency and productivity of the organization but also contributed to increasing the competitive advantage of the organization (Al-Dweiri et al., 2024). If the effectiveness of supply chain operations is not properly managed then it could lead to operational disruptions which could increase costs, and reduced competitiveness, particularly in dynamic environments like those faced by SMEs (Usmani et al., 2023). Additionally, mismanagement in this area could result in inefficiencies across production, procurement, and distribution which could weakens the supply chain operations performance (Abrokwah-Larbi & Awuku-Larbi, 2024). In this context, artificial intelligence (AI) become an important strategy for optimizing the company's operations (Basri, 2020). AI-based factors such as artificial intelligence-based risk management (AIRM), artificial intelligence-based innovation (AII), and generative artificial intelligence (GenAI) play an important role in driving improvements in supply chain operations performance through streamlining processes which are enabling data-driven decision-making, and increasing best operations process (Belhadi et al., 2024; Wong et al., 2024).

Among the above factors, AIRM is an important factor because it helps the organizations to identify potential risks which increases the firm's ability to mitigate challenges (Xu et al., 2024). Through leveraging data analytics, AIRM enhances risk assessment and management processes, which ultimately leads to more efficient operations (Shah et al., 2023). Similarly, artificial intelligence-based innovation (AII) also increases a culture of innovation which enables organizations to develop new products and services that enhance the existing offerings, and adapt to changing market conditions (Belhadi et al., 2024). On the other hand, generative AI also further strengthens these benefits by enabling creative problem-solving for innovations (Hirosawa et al., 2024). These previous studies have shown that AI-driven factors collectively contribute to increased supply chain operations performance by enhancing agility, responsiveness, and overall effectiveness to meet customer demands.

Moreover, through increasing the factors like operations adaptive capabilities (OAC) and operations ambidexterity innovation (OMI) the supply chain operations performance increased (Cheah & Tan, 2024; Mikalef et al., 2020). The strengthening of OAC enables organizations to respond to disruptions more effectively, allowing them to maintain a competitive edge. Additionally, focusing on OMI increases the balance between exploring new avenues and exploiting existing capabilities (Fawad Sharif et al., 2024). This dual approach enhances overall operational efficiency and effectiveness which ensures that companies can adapt to changing market conditions while maximizing their current resources (Basri, 2020). Through the integration of AI technologies and the enhancement of these critical operational factors, SMEs in Saudi Arabia can better navigate challenges and capitalize on growth opportunities that could lead to an increase the superior operational performance (Badghish & Soomro, 2024). Thus, focusing on the previous discussion, the study pays attention to the impact of AI-based factors on supply chain performance through OMI and OAC.

Several empirical studies have been conducted on AI-based factors, OMI, OAC, and supply chain operations performance, but there is a lack of research examining the

interconnected relationships among AIRM, AII, and GenAI in the context of Saudi Arabian SMEs (Basri, 2020; Malhotra, 2018). Most of the existing literature tends to focus on singular AI factors without considering how combining these technologies interact to enhance supply chain operational performance (Mikalef et al., 2023; Wu & Monfort, 2023). Thus, these studies indicated a need for a comprehensive research framework that integrates multiple dimensions of AI and their effect on the supply chain operations performance which is allowing for a deeper understanding of how these factors can be leveraged synergistically to drive organizational success. Furthermore, the role of operational adaptive capabilities and ambidexterity innovation as a mediating effect remains underexplored, which highlights an opportunity for researchers to develop models that capture these complex interactions (Abrokwah-Larbi & Awuku-Larbi, 2024; Ahmad et al., 2023). On the other hand, SMEs in Saudi Arabia are increasingly aware of the potential benefits of AI technologies but there is limited empirical evidence on how to effectively implement these systems to achieve enhanced supply chain operational performance (Abrokwah-Larbi & Awuku-Larbi, 2024; Mariani et al., 2023; Sullivan & Wamba, 2024). Research is scarce in the context of Saudi Arabia which demonstrates a successful implementation of these AI-driven practices in SMEs. Addressing these theoretical, practical, and contextual gaps, the study aimed to test the impact of AI-based factors on supply chain operations performance with the mediating of OAC and OMI in the context of Saudi Arabian SMEs.

The study with the study objective has significant contributions. Firstly, study through integrating AI dimensions with supply chain operational performance, this research contributes to the theoretical framework surrounding AI implementation in SMEs of Saudi Arabia. Additionally, study also highlights the mediating influence of operations adaptive capabilities and operations ambidexterity innovation in strengthening the relationship between AI indicators and supply chain outcomes, the findings offer practical insights for SME leaders and decision-makers, equipping them with actionable strategies to leverage AI technologies effectively and enhance their operational efficiency. As Saudi Arabia continues to pursue its Vision 2030 initiative, this study not only supports the academic community by providing a comprehensive understanding of AI's role in supply chain operations performance but it also raises economic growth through guiding SMEs in navigating the complexities of digital transformation.

2. Hypothesis Development

Artificial intelligence based risk management (AIRM) has enabled new approaches to risk management using powerful machine learning algorithms (Khanna et al., 2021). By analyzing vast troves of organizational data, AI systems can identify obscure risk factors and anticipate disruptive events that human analysts might overlook (Iftikhar et al., 2020). However, accurately assessing risk severity and ensuring preventative measures are effective requires a depth of understanding that only comes from experience (Iftikhar et al., 2020). For AI to offer truly helpful solutions, its recommendations must demonstrate nuanced consideration of both operational impacts and long-term consequences (Zahedi et al., 2023). While predictive analytics promise early warnings, balancing accordance and adaption across teams takes wisdom that AI is just beginning to attain. For now, the most prudent path may

integrate machine insight with human oversight, merging our respective strengths (Wong et al., 2024). They also further argued that AIRM also has a greater potential in increasing the corporate operations through the minimizing interruptions and optimizing effectiveness (Wong et al., 2024). Other authors also recommended that if the organization want to achieve their competitive advantage and gain operations performance then the companies should focus on AIRM (Farrokhi et al., 2024).

Empirically, Farrokhi et al. (2024) conducted study and found that AIRM is a significant predictors to increase supply chain operational performance through improving inventory management and predicting market shifts, which helped firms to avoid supply disruptions and maintain steady operations. In the same vein, Wamba-Taguimdje et al. (2020) also argued that predictive maintenance systems powered by AI reduced equipment failures and optimized maintenance schedules, which is directly contributing to improved supply chain operational performance. Another study by Claudino et al. (2019) in the financial sector found that AIRM improved operational security by detecting fraud and assessing credit risks in real time, leading to more efficient and secure transactions. Finally, Nwagwu et al. (2023) explored the application of AIRM in healthcare, where predictive analytics were used to anticipate patient needs and allocate resources effectively, thus improving the operational efficiency of hospitals. Based on previous discussion, it is hypothesized that,

H1: *Artificial intelligence-based risk management and its influence on operations performance.*

Furthermore, artificial intelligence-based innovation (AI-Innovation) which shown the usage of AI technologies to drive the new process development, product development and also in the improvement of services (Nwagwu et al., 2023). On the other hand, AI-Innovation focused on creating novel approaches to operational tasks that improve supply chain operational performance (Belhadi et al., 2024). AI-based innovation is also important for supply chain operations because it allows companies to automate complex tasks, optimize workflows, and develop new business models (Belhadi et al., 2024). Through integration of AI-driven innovations into their operations, organizations could also increase flexibility, reduce operational costs, and adapt more quickly to market changes (Belhadi et al., 2024). AII supports continuous improvement in operations through enhancing productivity and enabling businesses to discover more efficient ways of delivering value to their customers (Belhadi et al., 2024). Nwagwu et al. (2023) further empirically tested that the impact of AI-driven innovations to improve the inventory management through automated reordering systems and enhanced customer service with AI-powered chatbots, both of which led to operational performance. In the same vein, Wamba-Taguimdje et al. (2020) also examined the role of AI innovations and found that AII positively and significantly effecting to the supply chain operations performance (Mariani et al., 2023) investigated logistics operations, showing how AI innovations like autonomous delivery vehicles and AI-based route optimization systems improved delivery times and reduced fuel consumption, resulting in better operational performance. Additionally, Liu et al. (2020) found that AI-based innovations in the telecommunications industry streamlined network management operations by automating troubleshooting processes, which improved network reliability and reduced downtime. Based on previous discussion, it is hypothesized that,

H2: *Artificial intelligence-based innovation and its influence on operations performance.*

The generative artificial intelligence (GENAI) consisted of providing an AI system which helps to create a new content and new designs on the existing data. Other authors, argued that it consisted of large language models, generative adversarial networks, and AI-based content creation tools that could produce designs, and images (Ooi et al., 2023). Other authors also recommended that GEAI also significantly enhances supply chain operations performance through enabling automation in creative tasks, optimizing design processes, and generating innovative solutions (Yu & Guo, 2023). With the ability to create data-driven models and simulations, generative AI can improve decision-making and streamline operations which is leading to reduced time-to-market, higher product quality, and more efficient processes (Baidoo-Anu & Ansah, 2023). Yu and Guo (2023) also highlighted significant impact of GEN-AI on the supply chain operations where generative AI was used to automate product design, allowing companies to speed up the development process while maintaining high product quality, thereby improving operational performance. Yu and Guo (2023) explored the marketing sector, where generative AI tools created personalized content for large-scale marketing campaigns, reducing the time and cost of content production while improving customer engagement. Zhang et al. (2021) examined the use of generative AI in architecture and engineering, where AI systems generated optimized designs for structures, significantly reducing the time and resources needed for project completion, which enhanced overall operational efficiency. They also found the significant impact of GEN-AI on supply chain performance. Based on previous discussion, it is hypothesized that,

H3: *Generative artificial intelligence positively influences operations performance.*

The previous studies shown that AIRM has significant impact on supply chain operational performance but these studies still have various gaps that could be addressed in current study. Previous relations are inconsistent and AIRM also has significant impact on adaptive capabilities. Sullivan and Wamba (2024) found that AI-based risk management has significant impact on adaptive capabilities. Benis et al. (2018) also found that AI-based predictive maintenance systems enable businesses to predict equipment failure, thereby reducing downtime and improving response times in the business environment. Verma and Singhal (2023) argue that intelligent risk management tools help financial institutions adapt to rapid changes by providing real-time assessment and improving operational flexibility. As AI-based risk management increases efficiency, companies can maintain high performance in a variety of situations. This change allows companies to reduce downtime, reduce disruption, and increase productivity. For instance, companies could able to quickly adapt to unforeseen events such as product outages or equipment failures, re-efficiently restructuring processes and directly improving performance (Zhan et al., 2024). Further, studies were conducted to test the impact of AIRM on supply chain operations. They also argued that their relationship could be tested in the future with mediating or other relationships (Khasawneh et al., 2024; Wong et al., 2024). Other researchers Gikay (2024) also argued that AIRM increases the supply chain operations performance when the adaptive capabilities of the organizations are also increased. Thus, based on the previous, the following hypothesis is formulated below,

H4: *Artificial intelligence-based risk management significantly influences operations performance through operational adaptive capabilities.*

Similar to the above, AI-based innovation also helps firms' operations adaptive

capabilities by providing new tools that increase flexibility in the organizations (Li & Xu, 2023; Sullivan & Wamba, 2024). Belhadi et al. (2024)also found that companies that are using AI-powered inventory management systems can better adjust their supply chains based on real-time data and therefore be more flexible to business changes. Nwagwu et al. (2023) also suggested that using AI in manufacturing companies for analysis can quickly adjust production plans and allocate resources, thereby improving operational efficiency. Wamba et al. (2024) further stated that AI innovations, such as automated fraud detection systems, improve companies' ability to respond to changes in the market, leading to a complete transformation of the business copy. In addition, Wamba et al. (2024) AI-based innovation increases businesses' flexibility, directly supporting operational improvement. Instant improvements through AI innovation can help businesses improve processes, reduce operational inefficiencies, and improve performance outcomes. Further study of Nwagwu et al. (2023) highlighted the positive AI-based innovations to improve the supply chain operational performance and they further recommended that further relationships could be tested with the mediating or moderating effect. Based on previous discussion, it is hypothesized that,

H5: *Artificial intelligence-based innovation significantly influences operations performance through operational adaptive capabilities.*

Generative AI increases the supply chain operations performance has been found in various empirical studies. In the same context, further researchers has been conducted on the impact of generative AI on the operation's adaptive capabilities. For instance, Banala (2024) found that generative AI enables companies to rapidly create new products and allows them to quickly adjust manufacturing processes. wael Al-khatib et al. (2024) reported that AI increases discovery process by rapidly generating molecular models, thereby increasing the flexibility of R&D activities. In addition, generative AI increases the business flexibility required to improve performance. Companies that leverage generative AI can instantly streamline their operations from production to manufacturing, improve distribution, and better meet customer needs (Heiska, 2024). This increased flexibility leads to better performance, increased productivity, and increased efficiency. Further studies also conducted on the impact of generative AI on supply chain operations performance (Fosso Wamba et al., 2024). They also argued that further research could be explored in other context with the mediating or moderating effect. In other study, Gupta et al. (2024) theorize that generative AI could improve the company's performance when the organizations are more focused on the improvement of operations adaptive capabilities. Therefore, based on previous discussion, it is hypothesized that

H6: *Generative artificial intelligence significantly influences operations performance through operational adaptive capabilities.*

AI risk management is active in promoting innovations then it could refer to increasing the organization's ability to explore opportunities. Dong and Fan (2024) also found the positive impact of AI-based risk management on the Ambidextrousness innovations. They also argued that AI-based risk management allows organizations to balance short-term risk with long-term innovation, thereby improving their ability to manage risk discovery and innovation. In the same vein, Zhang and Suntrayuth (2024) also emphasized that companies that use AI to better manage financial risks could invest in new businesses by focusing on operations ambidextrousness capabilities. Kadhem et al. (2021) also showed that AI-based risk management enables

organizations in weak markets to develop new products while maintaining their current operations, thus operations ambidextrousness innovations. AI-based risk management improves operational efficiency through improving multi-faceted innovation in business, allowing companies to pursue both efficiency and innovation at the same time (Lee et al., 2023; Shaheed et al., 2023). This dual capability enables the organization to adapt to changes in the business environment while maintaining high performance in key areas. Ambidextrousness directly leads to increased performance, such as productivity, performance, and flexibility, as it enables businesses to explore new ways to grow without disrupting existing processes (sijabat et al., 2022). Further study on the impact of AI risk management on supply chain operations performance has been conducted and found a significant impact on supply chain operations performance (Wong et al., 2024). They also argued that further research could be explored in other contexts and with another effect. Therefore, a study has formulated the following research hypothesis below.

H7: *Artificial intelligence-based risk management significantly influences operations performance through operations ambidexterity innovation.*

Artificial intelligence is also an important indicator to increase the innovations of the organizations. For example, Sullivan and Wamba (2024) have shown that companies that have acquired intellectual skills for innovation management can introduce new technologies while improving existing processes which improves ambidexterity innovation. Sahoo et al. (2024) found that intelligence-based innovation processes in manufacturing allow companies to innovate quickly without affecting firm performance, thereby improving repair research and efforts. Additionally, Shang et al. (2024) show how AI-driven product innovation in technology companies encourages conflict by encouraging experimentation while refining core products. In other words, AI-based innovation will increase efficiency by improving multi-faceted innovation in business (Rashid et al., 2024). Companies that can innovate and improve their current operations are more profitable, competitive, and efficient (Cáceres-Huambo et al., 2022; Rathnayake & Gunawardana, 2023). Focusing on both exploration and implementation efforts allows organizations to work continuously while making daily operations more efficient, thereby improving overall performance. Further study was also conducted to test the impact of artificial intelligence-based innovation on performance(Rashid et al., 2024). They also argued that further research could be explored with another moderating or mediating effect. Therefore, a study has formulated the following research hypothesis,

H8: *Artificial intelligence-based innovation significantly influences operations performance through operations ambidexterity innovation.*

Generative AI has been found to significantly impact operations ambidexterity innovation by enabling firms to balance innovation with operational optimization. Empirically, Fosso Wamba et al. (2024) also established that generative AI tools in research and development helped companies to develop new products which helps to increase the firm's ability to pursue both exploratory and exploitative innovation. In the same vein, Sallam et al. (2024) also found that generative AI-enabled companies create new marketing strategies while improving ambidexterity innovations. Martin and Graulich (2024) further stated that generative AI allowed firms to innovate rapidly in their product development while maintaining stringent regulatory compliance in their ongoing operations. In another study, Martin and Graulich (2024)

it is also recommended that generative AI could increase supply chain operations performance through increasing operations ambidexterity innovation. Firms that utilize generative AI to balance new product development with process optimization are more agile and competitive, allowing them to innovate effectively without sacrificing operational efficiency (Wang & Zhang, 2024). The ambidextrous capabilities that generative AI supports help organizations maintain high productivity levels while exploring new growth opportunities, which directly improves overall performance (Rathnayake & Gunawardana, 2023). Further study was also conducted to test the impact of generative artificial on performance (Abumalloh et al., 2024). They also argued that further research could be explored with another moderating or mediating effect. Based on previous discussion, it is hypothesized that,

H9: *Generative artificial intelligence significantly influences operations performance through operations ambidexterity innovation*

3. Research Design and Survey Instrument

The study aimed to test the influence of artificial intelligence-based factors on supply chain operations performance. The study also tested the mediating effect of operations adaptive capabilities and operations ambidexterity. A quantitative research approach was employed to test the study hypothesis. This approach is considered to be better because it increases the generalized ability which allows for the analysis of trends across a large sample size (Brannen, 2017). Furthermore, researchers employed the cross-sectional research design which is used for the collection of data at a single point in time, which provides a snapshot of current conditions as compared to the longitudinal design (Rindfleisch et al., 2008). On the other hand, researchers used the survey method for cross-sectional data to gather standardized responses from participants, which enhanced the ability to compare data across respondents. Furthermore, the survey-based study is also effective as compared to the interview method because the survey enables data collection from a larger sample in a shorter period, with less interviewer bias, thereby improving the reliability and validity of the data (Kadian, 2022; Schwarz et al., 1998). Therefore, researchers employed the survey method for data collection in our study.

The survey instrument was adopted from extant studies. Adaptive capabilities comprised three items Belhadi et al. (2024), and supply chain operational performance also comprised five items which were adapted from the study of (wael Al-khatib et al., 2024). Artificial intelligence in innovation comprises 5 items (Belhadi et al., 2024). Artificial intelligence risk management is comprised of three items which are adapted from the (Dubey et al., 2021). These items were further also adapted in the study of (Wong et al., 2024). Generative artificial intelligence comprised five items and Ambidexterity innovations were also measured from five items. Both of the constructs were adopted from the study of (wael Al-khatib et al., 2024). These items were ranked on a point Likert Scale where 1 ranked strongly disagree and 5 for strongly agree. Study variables are predicted in Figure.1 below,

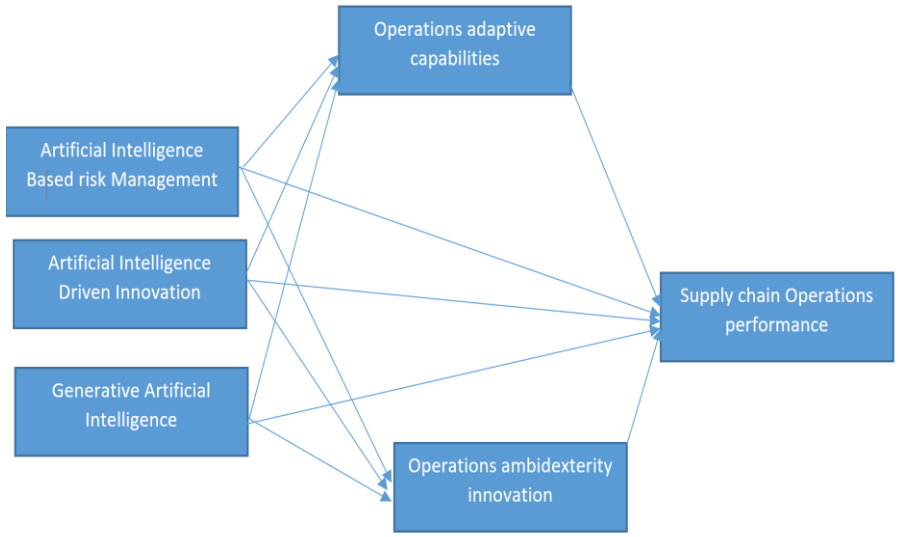

Figure.1: Research Framework

3.1 Sampling Technique and Data Collection Procedure

The population of the study was the employees of Saudi Arabia SMEs. From the population, data was collected using a convenient sampling technique from SME employees. The convenient sampling technique was chosen because it is more practical and easy to access for the participants, especially in a setting where time and resource constraints are a factor. Furthermore, the nonprobability sampling technique also helps to collect data quickly and effectively from the respondents (Etikan et al., 2016). Questionnaires were distributed among 450 employees which provided a strong basis for statistical analysis and increased the likelihood of diverse responses. Among these, 390 questionnaires were returned which yields a high response rate of approximately 87%. This large sample size strengthens the study's findings by enhancing the representativeness and reliability of the data, as it reduces sampling error and increases the statistical power of the analysis (Kotrlik & Higgins, 2001). Collected data was analyzed in two software's, SPSS and Smart PLS.

4. Data Analysis and Interpretation

4.1 Demographic Characteristics

The demographic table of the 350 employees from SMEs in Saudi Arabia reveals a predominantly male workforce (62.9%), with the largest age group being 26-35 years (42.9%), indicating a relatively young and dynamic employee base. Most respondents hold a Bachelor's degree (42.9%), followed by those with a Diploma (28.6%), suggesting a moderate to high level of education critical for adapting to AI technologies. Mid-level managers represent the largest group (42.9%), highlighting the involvement of experienced personnel in decision-making and operations. Additionally, a significant portion of the employees has 6-10 years of experience

(37.1%), contributing to a workforce that is practical, knowledgeable, and well-prepared for the integration of innovative processes, such as AI-driven solutions, within SMEs. The above results are predicted in Table.1 below,

Table 1: Demographic Characteristics

Demographic Variable	Category	Frequency (n)	Percentage (%)
Gender	Male	220	62.90%
	Female	130	37.10%
Age	18-25 years	50	14.30%
	26-35 years	150	42.90%
	36-45 years	100	28.60%
	Above 45 years	50	14.30%
Education Level	High School	70	20.00%
	Diploma	100	28.60%
	Bachelor's Degree	150	42.90%
	Master's Degree or Higher	30	8.50%
Position in Organization	Entry-level Employee	120	34.30%
	Mid-level Manager	150	42.90%
	Senior Manager/Executive	80	22.80%
Years of Experience	1-5 years	100	28.60%
	6-10 years	130	37.10%
	11-15 years	70	20.00%
	More than 15 years	50	14.30%

4.2 Reliability and Validity

The questionnaire was assessed through the measurement model employing Partial Least Square (PLS)-Structural Equation Modeling (SEM) technique and for evaluating the reliability and validity of construct following statistical test were employed. Firstly, the researchers employed the cronbach's Alpha which is a measure of internal consistency, with values above 0.700 generally indicating acceptable reliability (Bonett & Wright, 2015). Secondly, composite reliability which also shown the construct reliability and this values should be ideally exceed 0.700, which is affirming that the items consistently measure the intended concept (Ab Hamid et al., 2017). Thirdly, Average Variance Extracted (AVE) which assesses convergent validity and threshold value should be above 0.500 which is suggesting that the construct explains a significant portion of the variance in its items (Hair et al., 2017). As, researcher argued that above threshold values are important for ensuring that instrument which is used for the study yield reliable and valid results (Hair Jr et al., 2017). Therefore, predicted results is Table.2 shown that construct fulfill the requirement of convergent validity.

Table 2: Convergent validity

Constructs	Cronbach's Alpha	CR	AVE
AIRM	0.881	0.912	0.751
AII	0.852	0.891	0.723
GenAI	0.863	0.920	0.743
OAC	0.822	0.872	0.682
OMI	0.841	0.883	0.711
SCOP	0.891	0.921	0.773
R Square AMI		0.348	
R Square OAC		0.452	
R Square SCOP		0.672	
Q SQUARE SCOP		0.213	

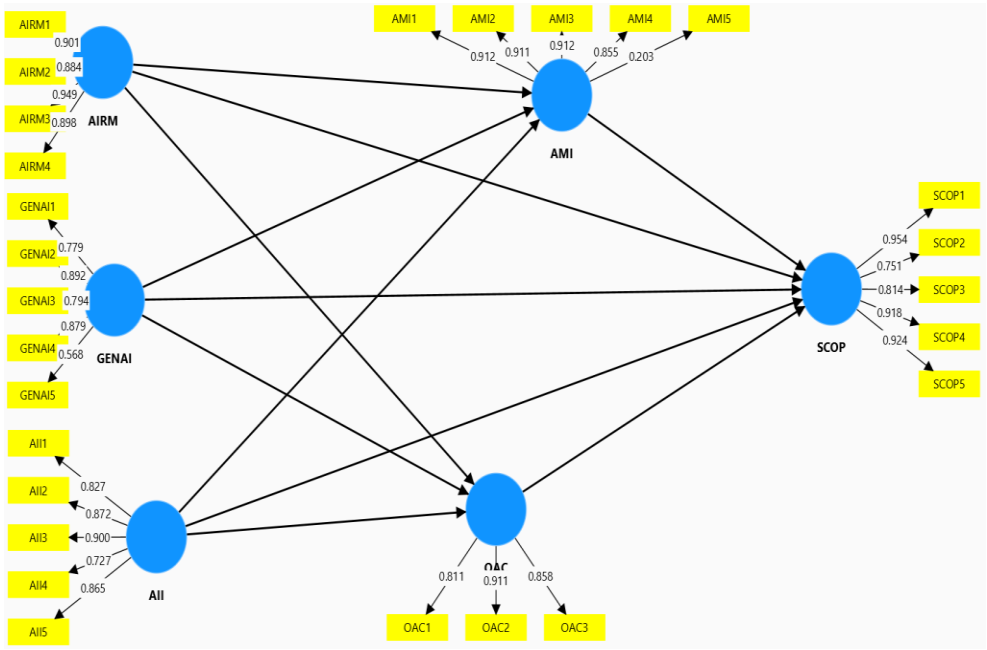

Figure 2: Measurement mode

When the convergent validity criteria is fulfilled from the construct, then next step is to fulfill the requirement of discriminant validity. The discriminant validity of construct is a critical aspect of construct which shown that construct is distinct from the others in the model (Rönkkö & Cho, 2022). The discriminant validity could be assessed through Fornell and Larcker, cross loadings, and discriminant validity (Henseler et al., 2015). Among these Fornell and Larcker is established when the square root of the AVE for each construct exceeds its correlations with other constructs (Henseler et al., 2015). In Table.3 discriminant validity values through Fornell and Larcker are presented which shown that all diagonal values represent the square roots of the AVE for each construct, while the off-diagonal values are the correlations among the constructs. The Table.3 predicted diagonal values are greater than from below which shown the discriminant validity of construct. For example, the square root of the AVE for AIRM is 0.866, which is significantly higher than its correlation coefficients with other constructs. This pattern is consistent across all construct which demonstrates that all construct values are greater from others. These established thresholds demonstrate that each construct is sufficiently distinct which shown the discriminant validity of the construct (Henseler et al., 2015). The above results are predicted in Table.3.

Table 3: Discriminant Validity

Constructs	VIF	AIRM	AII	GenAI	OAC	OMI	SCOP
AIRM	1.341	0.866					
AII	1.231	0.549	0.850				
GenAI	1.892	0.561	0.584	0.861			
OAC	1.341	0.492	0.482	0.505	0.825		
OMI	2.121	0.487	0.521	0.533	0.461	0.841	
SCOP	.....	0.612	0.654	0.622	0.547	0.578	0.877

4.3 Empirical Results

The R Square shown that in AMI model explains34.8% of the variance in AMI, 45.2% in OAC, and 67.2% in SCOP which shown the moderate to explanatory power for the SCOP. The Q-square value of 0.213 for SCOP shows a positive predictive relevance of the model for this variable (Hair Jr et al., 2017). The structural model results demonstrated that artificial intelligence based risk management (AIRM) shows a strong and significant influence on supply chain operational performance, with a beta coefficient (β = 0.430, t = 5.733) in the context of Saudi Arabian SMEs which supports to the first hypothesis. Furthermore, Artificial Intelligence-based Innovation (AII) also significantly and positively influence on supply chain operations performance (β = 0.510, t = 7.286), which is indicating that the integration of innovative AI technologies within SMEs is leading to improved operational outcomes which is supporting to the second hypothesis. Similarly, Generative Artificial Intelligence (GenAI) positively and significantly influences to supply chain operations performance (β = 0.460, t = 7.077), which is suggesting that AI-driven generative tools further enhance supply chain operations, which is supporting the third hypothesis. When considering the mediating effects of operations adaptive capabilities (OAC) and operations ambidexterity innovation (OMI), the results continue to highlight the importance of AI. AIRM, when mediated by OAC, significantly impacts supply chain operations performance (β = 0.380, t = 4.872), which is emphasizing the role of adaptive capabilities in linking AI-driven risk management to operational success. Similarly, AIImediated by OAC (β = 0.550, t = 7.971) and GenAI mediated by OAC (β = 0.470, t = 7.344) both demonstrate significant positive impacts, supporting the role of adaptive capabilities in maximizing the benefits of AI innovations on supply chain operational performance. Finally, when operations ambidexterity is considered as a mediator, AIRM (β = 0.420, t = 5.185), AII (β = 0.602, t = 8.824), and GenAI (β = 0.480, t = 7.742) all show strong positive effects on supply chain operational performance. This highlights the critical importance of operational ambidexterity in leveraging AI capabilities for improved performance in Saudi Arabian SME. The above results are predicted in Table.4 below.

Table 4: Regression Results

Hypothesis	Coefficient	Standard Error	t-statistic	p-value
AIRM → OP	0.430	0.075	5.733	0.000***
AII→ OP	0.510	0.071	7.286	0.000***
GenAI → OP	0.460	0.065	7.077	0.000***
AIRM → OAC → OP	0.380	0.078	4.872	0.000***
AII→ OAC → OP	0.550	0.069	7.971	0.000***
GenAI → OAC → OP	0.470	0.064	7.344	0.000***
AIRM → OMI→ OP	0.420	0.081	5.185	0.000***
AII→ OMI→ OP	0.602	0.068	8.824	0.000***
GenAI → OMI→ OP	0.480	0.062	7.742	0.000***

Note: AIRM: Artificial Intelligence-based Risk Management, AII: Artificial Intelligence-based Innovation, GenAI: Generative Artificial Intelligence, OAC: operations adaptive capabilities, OMI: Operations Ambidexterity Innovation, OP: operations performance.

5. Discussion

Study objective was to empirically test the influence of artificial intelligence-based factors on supply chain performance. The study also tested the mediating effect of

operations adaptive capabilities and operations ambidexterity. For this purpose, data was collected from 390 employees of SMEs in Saudi employing a convenient sampling technique. The hypothesis results show artificial intelligence-based risk management has a positive and significant impact on the supply chain operations performance of Saudi Arabia SMEs. This relationship in the context of Saudi Arabia shows that in SMEs AI-based risk management tools are more effective which are helping to increase the supply chain operations performance. As, for the SMEs is challenging to manage the risk with their limited resources and with higher vulnerability to external market shocks (Falkner & Hiebl, 2015). In contrast to this, AI risk management practices in Saudi Arabia offer a suitable ability to automate and streamline risk identification processes, providing real-time insights that allow businesses to act proactively rather than reactively. This finding is in line with Wong et al. (2024), who noted that AI technologies significantly reduce the margin for human error in risk assessment and provide more accurate forecasting models. Thus, based on these findings, it is argued that Saudi Arabia SMEs should leverage AI-based risk management that can mitigate operational risks related to supply chain disruptions, market volatility, and regulatory changes, which are common challenges in the region. Additionally, AIRM tools enable SMEs to allocate resources more effectively by identifying potential threats early, thus avoiding costly disruptions and improving overall performance.

Furthermore, artificial intelligence-based innovations also has positive and significant impact on the supply chain operational performance of SMEs in Saudi Arabia. This significant impact in the context of Saudi Arabia indicates that AI plays a crucial role in increasing innovation within SMEs. Innovation is key for SMEs looking to differentiate themselves in competitive markets, and AI technologies provide them with the tools to innovate across processes, products, and services. AI facilitates innovation by enhancing operational agility, enabling firms to quickly adapt to changing market conditions and customer preferences. The results are consistent with the results of (Belhadi et al., 2024), who argue that AI-driven innovation empowers SMEs to develop new business models and streamline processes, ultimately leading to better operational outcomes. These findings endorsed some implications in the context of Saudi Arabia, where economic diversification is a primary goal, AII is particularly important as it allows SMEs to explore new growth opportunities and achieve sustainability.

On the other hand, further results also show the positive and significant impact of generative artificial intelligence on the supply chain operations performance of SMEs in Saudi Arabia. These findings highlight the significance of AI tools which are creating automotive and operational processes to increase the operational performance of SMEs in Saudi Arabia. The results are particularly consistent with the studies of (Fosso Wamba et al., 2024) suggesting that generative AI technologies have the potential to revolutionize operations by automating routine tasks while allowing businesses to focus on strategic innovation. In Saudi Arabia, where many SMEs are involved in sectors that require high levels of customization and customer engagement, generative AI, such as tools used in design, marketing, and customer engagement enables SMEs to enhance their creativity and efficiency without the need for extensive resources. Furthermore, these findings are also particularly beneficial for SMEs in sectors like retail, manufacturing, and service industries, where rapid response as per the market trends is critical which can increase the competitive advantage of the organizations.

Further mediating effect results show that operations adaptive capabilities partially mediated between artificial intelligence-based risk and supply chain operations performance. These results show the importance of operations adaptive capabilities as a mediator between AI-based risk management and supply chain operations performance. The results are in line with the study of (Kuo, 2024; Wong et al., 2024) where they argued that adaptive capabilities are essential for SMEs operating in volatile markets, as they allow firms to continuously innovate and reallocate resources efficiently. In this regard, these findings emphasized the significance for Saudi Arabian SMEs in developing flexibility and agility. Further, OAC also partially mediated between AI-based innovations and supply chain operations performance of SMEs in Saudi Arabia. These results show that SMEs in Saudi Arabia are playing a crucial role in the enhancement of AI-based innovations which is supporting to increase the supply chain operations performance. These results are further in line with the results of Belhadi et al. (2024) where they also found the partial mediating effect of OAC and they further argued that OAC could be used as a mediating effect in other contexts. Therefore, study findings are supported by previous studies. Therefore, it is argued that SMEs should focus on fully capitalizing on AI technologies which help to increase OAC in their businesses to rapidly adjust their operations in response to changing market conditions or internal challenges which could lead to improve the operation's long-term sustainability. Further partial mediating effects of OAC were also found in the relationship between generative AI and supply chain operations performance in the context of Saudi Arabian SMEs. These findings are supported by the results of (Acosta-Prado & Tafur-Mendoza, 2024), where they also found the significant mediating effect of OAC.

Lastly, operations ambidexterity innovations (OMI) also partially mediated the relationship between AI-based factors and the supply chain operational performance of SMEs in Saudi Arabia. This significant mediating effect of OMI suggested that ambidextrous organizations that balance operational efficiency with the pursuit of new opportunities are better equipped to leverage AI for enhanced performance. The results are similar to the findings of (Dong & Fan, 2024; wael Al-khatib et al., 2024) where they highlighted that AI enables businesses to operate ambidextrously by improving decision-making processes, allowing firms to exploit existing capabilities while exploring innovative solutions. Therefore, based on the findings it is suggested that for MSEs in Saudi Arabia, ambidexterity is crucial as it allows them to capitalize on current operational strengths while remaining open to new opportunities in the rapidly evolving marketplace. AI tools through providing real-time data and insights help any business strike a balance between maintaining operational efficiency and pursuing innovations, which is key to sustaining long-term growth. It is also enforced to the Saudi Arabian SMEs to focus on AI factor to increase their innovations in their business that could increase their operational efficiency and also increase competitive advantage of the business.

6. Implications and Future Directions

The study has various theoretical and practical implications. Theoretically, this study makes significant contributions in the extant literature through exploring the impact of AI based factors on supply chain operations performance with the mediating effect of operations adaptive capabilities and operations ambidexterity innovations in

the context of SMEs in Saudi Arabia. To the researchers' best knowledge, this is the first time an AI-based model incorporating AI-based Risk Management, AI based innovations, and generative AI has been tested in Saudi SMEs. The findings contribute to a deeper understanding of how AI technologies can transform operational outcomes in smaller firms within emerging markets. On the other hand, through introducing operations adaptive capabilities and operations ambidexterity innovation as a mediators, the study enriches existing knowledge on how organizational flexibility and ambidexterity enhance the positive effects of AI on SME performance. Lastly, the significant findings of the study also contributed to explore a new research area for future research for other researchers to conduct their research in the area AI and supply chain operations performance across different cultural and economic contexts.

Along with theoretical contributions, study holds some practical contributions in the context of Saudi Arabia SMEs managers, owners and policy makers. The study with significant findings contributed that adopting AI technologies can significantly enhance supply chain operational efficiency. Further, practical implications also highlighted the need for SMEs to not only integrate AI but also to build adaptive and ambidextrous capabilities to fully exploit AI's potential. In the context of Saudi Arabia's Vision 2030, this research provides actionable recommendations for promoting AI adoption through government support, training programs, and incentives that encourage innovation and technology-driven growth in SMEs. Lastly, current research contributes to present a pioneering model for AI implementation in Saudi SMEs, which is offering a framework that could be adapted by SMEs in other regions aiming for supply chain operations performance.

The study with significant contributions still have various limitations that could be addressed in further research to increase the new research avenue for further researchers. Firstly, study limited to one country SMEs that could be generalized on other countries and on other sectors. Therefore, further research could be conducted on other large scale companies and on other countries to increase the variations in results. Secondly, study limited on cross sectional research where data collected on one time which finding could not be generalied on findings of longitudinal research design. In this regards, further research could be explored on longitudinal research design. Lastly, the study focused only on mediating effects while ignored moderating effects like organizational culture, or process automation that could strengthen the relationship between AI-based factors and supply chain operations performance. Therefore, future research could be extended with the moderating effect of process automation to increase the predictive power of the model.

7. Conclusion

The research objective was to test the impact of artificial intelligence-based factors on supply chain performance. The survey-based study used the cross-sectional research design, and Partial Least Square-Structural Equation Modeling (PLS-SEM). The structural model results show that AI-based risk management, AI-based innovations, and generative AI have a positive and significant impact on supply chain performance. On the other hand, indirect mediating effect results also show that operations adaptive capabilities and operations ambidexterity innovation positively

and significantly mediated among all AI-based indicators and supply chain performance of SMEs in Saudi Arabia. The study on the findings of AI-based factors to improve supply chain operations contributed empirical literature in the context of Saudi Arabian SMEs. Furthermore, the study also highlighted the mediating effect of operations adaptive capabilities and operations ambidexterity innovation in strengthening the relationship between AI indicators and supply chain outcomes. These findings provide valuable insights for SMEs seeking to leverage AI technologies to improve supply chain operational performance.

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References

Ab Hamid, M. R., Sami, W., & Sidek, M. M. (2017). Discriminant validity assessment: Use of Fornell & Larcker criterion versus HTMT criterion. Journal of physics: Conference series, 1742-6596. https://doi.org/10.1088/1742-6596/890/1/012163

Abrokwah-Larbi, K., & Awuku-Larbi, Y. (2024). The impact of artificial intelligence in marketing on the performance of business organizations: evidence from SMEs in an emerging economy. *Journal of Entrepreneurship in Emerging Economies*, *16*(4), 1090-1117. https://doi.org/10.1108/JEEE-07-2022-0207

Abumalloh, R. A., Nilashi, M., Ooi, K. B., Tan, G. W. H., & Chan, H. K. (2024). Impact of generative artificial intelligence models on the performance of citizen data scientists in retail firms. *Computers in Industry*, *161*, 104128. https://doi.org/10.1016/j.compind.2024.104128

Acosta-Prado, J. C., & Tafur-Mendoza, A. A. (2024). Examining the mediating role of dynamic capabilities in the relationship between information and communication technologies and sustainable performance. *VINE Journal of Information and Knowledge Management Systems*, *54*(3), 561-577. https://doi.org/10.1108/VJIKMS-10-2021-0257

Ahmad, H., Hanandeh, R., Alazzawi, F., Al-Daradkah, A., ElDmrat, A., Ghaith, Y., & Darawsheh, S. (2023). The effects of big data, artificial intelligence, and business intelligence on e-learning and business performance: Evidence from Jordanian telecommunication firms. *International Journal of Data and Network Science*, *7*(1), 35-40. http://dx.doi.org/10.5267/j.ijdns.2022.12.009

Al-Dweiri, M., Ramadan, B., Rawshdeh, A., Nassoura, A., Al-Hamad, A., & Ahmad, A. (2024). The mediating role of lean operations on the relationship between supply chain integration and operational performance. *Uncertain Supply Chain Management*, *12*(2), 1163-1174. http://dx.doi.org/10.5267/j.uscm.2023.11.017

Badghish, S., & Soomro, Y. A. (2024). Artificial intelligence adoption by SMEs to achieve sustainable business performance: application of technology–organization–environment framework. *Sustainability*, *16*(5), 1864. https://doi.org/10.3390/su16051864

Baidoo-Anu, D., & Ansah, L. O. (2023). Education in the era of generative artificial intelligence (AI): Understanding the potential benefits of ChatGPT in promoting teaching and learning. *Journal of AI*, *7*(1), 52-62. https://doi.org/10.61969/jai.1337500

Banala, S. (2024). The Future of IT Operations: Harnessing Cloud Automation for Enhanced Efficiency and The Role of Generative AI Operational Excellence. *International Journal of Machine Learning and Artificial Intelligence*, *5*(5), 1-15. https://jmlai.in/index.php/ijmlai/article/view/42

Basri, W. (2020). Examining the impact of artificial intelligence (AI)-assisted social media marketing on the performance of small and medium enterprises: toward effective business management in the Saudi Arabian context. *International Journal of Computational Intelligence Systems*, *13*(1), 142-152. https://doi.org/10.2991/ijcis.d.200127.002

Belhadi, A., Mani, V., Kamble, S. S., Khan, S. A. R., & Verma, S. (2024). Artificial intelligence-driven innovation for enhancing supply chain resilience and performance under the effect of supply chain dynamism: an empirical investigation. *Annals of Operations Research*, *333*(2), 627-652. https://doi.org/10.1007/s10479-021-03956-x

Benis, A., Notea, A., & Barkan, R. (2018). Risk and disaster management: from planning and expertise to smart, intelligent, and adaptive systems. In *Building Continents of Knowledge in Oceans of Data: The Future of Co-Created eHealth* (pp. 286-290). IOS Press. https://doi.org/10.3233/978-1-61499-852-5-286

Bonett, D. G., & Wright, T. A. (2015). Cronbach's alpha reliability: Interval estimation, hypothesis testing, and sample size planning. *Journal of organizational behavior*, *36*(1), 3-15. https://doi.org/10.1002/job.1960

Brannen, J. (2017). Combining qualitative and quantitative approaches: an overview. *Mixing methods: Qualitative and quantitative research*, 3-37. https://doi.org/10.4324/9781315248813

Cáceres-Huambo, A., Vargas, J. M. E., Rivera, J. A. F., & Mamani-Concha, M. P. (2022). Antifungal effect of foeniculum vulgare mill essential oil on strains of Candida albicans in vitro. *Journal of Natural Science, Biology and Medicine*, *13*(2). https://doi.org/10.4103/jnsbm.JNSBM_13_2_2

Cheah, S. C., & Tan, C. L. (2024). External knowledge sourcing, organizational ambidexterity and manufacturing performance: a new insight for dynamic operation management. *Benchmarking: An International Journal*, *31*(5), 1643-1666. https://doi.org/10.1108/BIJ-11-2022-0695

Claudino, J. G., Capanema, D. d. O., de Souza, T. V., Serrão, J. C., Machado Pereira, A. C., & Nassis, G. P. (2019). Current approaches to the use of artificial intelligence for injury risk assessment and performance prediction in team sports: a systematic review. *Sports medicine-open*, *5*, 1-12. https://doi.org/10.1186/s40798-019-0202-3

Dong, W., & Fan, X. (2024). Research on the Influence Mechanism of Artificial Intelligence Capability on Ambidextrous Innovation. *Journal of Electrical Systems*, *20*(3), 246-262. https://doi.org/10.52783/jes.2378

Dubey, R., Bryde, D. J., Foropon, C., Tiwari, M., Dwivedi, Y., & Schiffling, S. (2021). An investigation of information alignment and collaboration as complements to supply chain agility in humanitarian supply chain. *International Journal of Production Research*, *59*(5), 1586-1605. https://doi.org/10.1080/00207543.2020.1865583

Etikan, I., Musa, S. A., & Alkassim, R. S. (2016). Comparison of convenience sampling and purposive sampling. *American journal of theoretical and applied statistics*, *5*(1), 1-4. https://doi.org/10.11648/j.ajtas.20160501.11

Falkner, E. M., & Hiebl, M. R. (2015). Risk management in SMEs: a systematic review of available evidence. *The Journal of Risk Finance*, *16*(2), 122-144. https://doi.org/10.1108/JRF-06-2014-0079

Farrokhi, M., Khouzani, S. J., Farrokhi, M., Jalayeri, H., Faranoush, P., Babaei, M., Nouri, S., SalekShahabi, M., Taghipour, M. J., & Tavakoli, F. (2024). Artificial Intelligence and Deep Learning for Screening and Risk Assessment of Cancers. *Kindle*, *4*(1), 1-140. http://dx.doi.org/10.5281/zenodo.10458369

Fawad Sharif, S. M., Yang, N., ur Rehman, A., Alghamdi, O., & Kanwal, T. (2024). SMEs' sustainable innovation performance during pandemic: impact of knowledge coupling and parallel-mediation of ambidexterity and market capitalising agility. *Technology analysis & strategic management*, *36*(10), 2489-2503. https://doi.org/10.1080/09537325.2022.2153029

Fosso Wamba, S., Guthrie, C., Queiroz, M. M., & Minner, S. (2024). ChatGPT and generative artificial intelligence: an exploratory study of key benefits and challenges in operations and supply chain management. *International Journal of Production Research*, *62*(16), 5676-5696. https://doi.org/10.1080/00207543.2023.2294116

Gikay, A. A. (2024). Risks, innovation, and adaptability in the UK's incrementalism versus the European Union's comprehensive artificial intelligence regulation. *International Journal of Law and Information Technology*, *32*(1), eaae013. https://doi.org/10.1093/ijlit/eaae013

Gupta, R., Nair, K., Mishra, M., Ibrahim, B., & Bhardwaj, S. (2024). Adoption and impacts of generative artificial intelligence: Theoretical underpinnings and research agenda. *International Journal of Information Management Data Insights*, *4*(1), 100232. https://doi.org/10.1016/j.jjimei.2024.100232

Hair, J., Hollingsworth, C. L., Randolph, A. B., & Chong, A. Y. L. (2017). An updated and expanded assessment of PLS-SEM in information systems research. *Industrial management & data systems*, *117*(3), 442-458. https://doi.org/10.1108/IMDS-04-2016-0130

Hair Jr, J. F., Matthews, L. M., Matthews, R. L., & Sarstedt, M. (2017). PLS-SEM or CB-SEM: updated guidelines on which method to use. *International Journal of Multivariate Data Analysis*, *1*(2), 107-123. https://doi.org/10.1504/IJMDA.2017.087624

Heiska, O. (2024). Use of generative artificial intelligence in business-to-business sales of industrial services in the machinery manufacturing industry: case studies from various machinery manufacturing industries. https://urn.fi/URN:NBN:fi-fe2024041216722

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the academy of marketing science*, *43*, 115-135. https://doi.org/10.1007/s11747-014-0403-8

Hirosawa, T., Harada, Y., Mizuta, K., Sakamoto, T., Tokumasu, K., & Shimizu, T. (2024). Diagnostic performance of generative artificial intelligences for a series of complex case reports. *Digital Health*, *10*, 20552076241265215. https://doi.org/10.1177/20552076241265215

Iftikhar, A., Musa, S., Alam, M., & Su'ud, M. M. (2020). Artificial intelligence based risk management in global software development: a proposed architecture to

reduce risk by using time, budget and resources constraints. *Journal of Computational and Theoretical Nanoscience*, *17*(2-3), 878-885. https://doi.org/10.1166/jctn.2020.8735

Kadhem, L. N. J., Kadhem, A. L. H. A., & Dawood, F. S. (2021). The Role of Artificial Intelligence in achieving Ambidextrous Performance A case study in a sample of private banks. *Journal of Accounting and Financial Studies (JAFS)*, *16*(special), 61-82. https://jpgiafs.uobaghdad.edu.iq/index.php/JAFS/article/view/1048

Kadian, R. (2022). University Students' unrest and Adjustment Problem with Students' Disengagement from the Course as a Mediator. *Transnational Marketing Journal*, *10*(3), 515-532. https://doi.org/10.33182/tmj.v10i3.2409

Khanna, E., Popli, R., & Chauhan, N. (2021). Artificial intelligence based risk management framework for distributed agile software development. 2021 8th International Conference on Signal Processing and Integrated Networks (SPIN), 166543564X. https://doi.org/10.1109/SPIN52536.2021.9566000

Khasawneh, Y. J. A., Khasawneh, M. A. S., Alkhasawneh, T., Alwaely, S. A., & Al-Barakat, G. A. M. (2024). Using smartphone applications to administer the educational process. *Arts Educa*, *39*. https://doi.org/10.58262/ArtsEduca.3907

Kotrlik, J., & Higgins, C. (2001). Organizational research: Determining appropriate sample size in survey research appropriate sample size in survey research. *Information technology, learning, and performance journal*, *19*(1), 43. https://www.researchgate.net/publication/200824035

Kuo, S.-Y. (2024). Improving innovation performance through learning capability and adaptive capability: The moderating role of big data analytics. *Knowledge Management Research & Practice*, *22*(4), 364-376. https://doi.org/10.1080/14778238.2023.2212182

Lee, K., Woo, H.-G., Park, T., & JONG, S. D. (2023). Managers'pursuit Of Ambidexterity In The Context Of Artificial Intelligence Implementations: Insights Into Situationally Induced Regulatory Focus. *International Journal of Innovation Management*, *27*(09n10), 2350051. https://www.worldscientific.com/doi/abs/10.1142/S1363919623500512

Li, B., & Xu, W. (2023). Legal Risk Prediction and Prevention and Control of Sports Event Rebroadcasting in the Internet Age. *Revista de Psicología del Deporte (Journal of Sport Psychology)*, *32*(4), 298-307. https://rpd-online.com/index.php/rpd/article/view/967

Liu, J., Chang, H., Forrest, J. Y.-L., & Yang, B. (2020). Influence of artificial intelligence on technological innovation: Evidence from the panel data of china's manufacturing sectors. *Technological Forecasting and Social Change*, *158*, 120142. https://doi.org/10.1016/j.techfore.2020.120142

Malhotra, Y. (2018). AI, machine learning & deep learning risk management & controls: beyond deep learning and generative adversarial networks: model risk management in AI, machine learning & deep learning: princeton presentations in AI-ML risk management & control systems (presentation slides). Machine Learning & Deep Learning: Princeton Presentations in AI-ML Risk Management & Control Systems (Presentation Slides)(April 21, 2018). Princeton Presentations in AI & Machine Learning Risk Management & Control Systems, 2018 Princeton Fintech & Quant Conference, Princeton University. https://dx.doi.org/10.2139/ssrn.3167035

Mariani, M. M., Machado, I., Magrelli, V., & Dwivedi, Y. K. (2023). Artificial intelligence

in innovation research: A systematic review, conceptual framework, and future research directions. *Technovation*, *122*, 102623. https://doi.org/10.1016/j.technovation.2022.102623

Martin, P. P., & Graulich, N. (2024). Navigating the data frontier in science assessment: Advancing data augmentation strategies for machine learning applications with generative artificial intelligence. *Computers and Education: Artificial Intelligence*, *7*, 100265. https://doi.org/10.1016/j.caeai.2024.100265

Mikalef, P., Islam, N., Parida, V., Singh, H., & Altwaijry, N. (2023). Artificial intelligence (AI) competencies for organizational performance: A B2B marketing capabilities perspective. *Journal of Business Research*, *164*, 113998. https://doi.org/10.1016/j.jbusres.2023.113998

Mikalef, P., Krogstie, J., Pappas, I. O., & Pavlou, P. (2020). Exploring the relationship between big data analytics capability and competitive performance: The mediating roles of dynamic and operational capabilities. *Information & Management*, *57*(2), 103169. https://doi.org/10.1016/j.im.2019.05.004

Nwagwu, U., Niaz, M., Chukwu, M. U., & Saddique, F. (2023). The influence of artificial intelligence to enhancing supply chain performance under the mediating significance of supply chain collaboration in manufacturing and logistics organizations in Pakistan. *Traditional Journal of Multidisciplinary Sciences*, *1*(02), 29–40-29–40. https://www.researchgate.net/publication/373864751

Ooi, K.-B., Tan, G. W.-H., Al-Emran, M., Al-Sharafi, M. A., Capatina, A., Chakraborty, A., Dwivedi, Y. K., Huang, T.-L., Kar, A. K., & Lee, V.-H. (2023). The potential of generative artificial intelligence across disciplines: Perspectives and future directions. *Journal of Computer Information Systems*, 1-32. https://doi.org/10.1080/08874417.2023.2261010

Rashid, A., Baloch, N., Rasheed, R., & Ngah, A. H. (2024). Big data analytics-artificial intelligence and sustainable performance through green supply chain practices in manufacturing firms of a developing country. *Journal of Science and Technology Policy Management*. https://doi.org/10.1108/JSTPM-04-2023-0050

Rathnayake, C., & Gunawardana, A. (2023). The role of generative ai in enhancing human resource management recruitment, training, and performance evaluation perspectives. *International Journal of Social Analytics*, *8*(11), 13-22. https://norislab.com/index.php/ijsa/article/view/53

Rindfleisch, A., Malter, A. J., Ganesan, S., & Moorman, C. (2008). Cross-sectional versus longitudinal survey research: Concepts, findings, and guidelines. *Journal of marketing research*, *45*(3), 261-279. https://doi.org/10.1509/jmkr.45.3.261

Rönkkö, M., & Cho, E. (2022). An updated guideline for assessing discriminant validity. *Organizational Research Methods*, *25*(1), 6-14. https://doi.org/10.1177/1094428120968614

Sahoo, S., Kumar, S., Donthu, N., & Singh, A. K. (2024). Artificial intelligence capabilities, open innovation, and business performance–Empirical insights from multinational B2B companies. *Industrial Marketing Management*, *117*, 28-41. https://doi.org/10.1016/j.indmarman.2023.12.008

Sallam, M., Al-Mahzoum, K., Alshuaib, O., Alhajri, H., Alotaibi, F., Alkhurainej, D., Al-Balwah, M. Y., Barakat, M., & Egger, J. (2024). Language discrepancies in the performance of generative artificial intelligence models: an examination of infectious disease queries in English and Arabic. *BMC Infectious Diseases*, *24*(1), 1-13. https://doi.org/10.1186/s12879-024-09725-y

Saragih, J., Tarigan, A., Silalahi, E. F., Wardati, J., & Pratama, I. (2020). Supply chain operational capability and supply chain operational performance: Does the supply chain management and supply chain integration matters. *Int. J Sup. Chain. Mgt Vol*, *9*(4), 1222-1229. https://www.researchgate.net/publication/344426743

Schwarz, N., Groves, R. M., & Schuman, H. (1998). Survey methods. *The handbook of social psychology*, *1*, 143-179. https://www.researchgate.net/publication/232562918

Shah, H. M., Gardas, B. B., Narwane, V. S., & Mehta, H. S. (2023). The contemporary state of big data analytics and artificial intelligence towards intelligent supply chain risk management: a comprehensive review. *Kybernetes*, *52*(5), 1643-1697. https://doi.org/10.1108/K-05-2021-0423

Shaheed, J. M., Alabdily, D. H., & Amanah, A. A. (2023). 202 Strategic Physiognomy and Its Impact on Acheiving Outstanding Performance. *International Journal of eBusiness and eGovernment Studies*, *15*(3), 86-104. https://doi.org/10.34111/ijebeg.2023150305

Shang, Y., Zhou, S., Zhuang, D., Żywiołek, J., & Dincer, H. (2024). The impact of artificial intelligence application on enterprise environmental performance: Evidence from microenterprises. *Gondwana Research*, *131*, 181-195. https://doi.org/10.1016/j.gr.2024.02.012

Sijabat, E. A. S., Nimran, U., Utami, H. N., & Prasetya, A. (2022). The impact of ambidextrous innovation on the performance and competitiveness of start-up companies: an empirical study from Indonesia. *The Journal of Asian Finance, Economics and Business*, *9*(1), 25-34. https://doi.org/10.13106/jafeb.2022.vol9.no1.0025

Sullivan, Y., & Wamba, S. F. (2024). Artificial intelligence and adaptive response to market changes: A strategy to enhance firm performance and innovation. *Journal of Business Research*, *174*, 114500. https://doi.org/10.1016/j.jbusres.2024.114500

Usmani, A., Sharma, M., Bung, P., Kumar, R., Ahmad, F., & Gupta, A. (2023). Key Variables Influencing Artificial Intelligence (AI) Implementation In Supply Chain Management (SCM): An Empirical Analysis On Smes. *Migration Letters*, *20*(S11), 1284-1307. https://ssrn.com/abstract=4759869

Verma, A., & Singhal, N. (2023). Integrating Artificial Intelligence for Adaptive Decision-Making in Complex System. International Conference on Advances in Data-driven Computing and Intelligent Systems, Springer. 95-105. https://doi.org/10.1007/978-981-99-9521-9_8

Wael Al-khatib, A., Moh'd Anwer, A.-S., & Khattab, M. (2024). How can generative artificial intelligence improve digital supply chain performance in manufacturing firms? Analyzing the mediating role of innovation ambidexterity using hybrid analysis through CB-SEM and PLS-SEM. *Technology in Society*, *78*, 102676. https://doi.org/10.1016/j.techsoc.2024.102676

Wamba-Taguimdje, S.-L., Wamba, S. F., Kamdjoug, J. R. K., & Wanko, C. E. T. (2020). Influence of artificial intelligence (AI) on firm performance: the business value of AI-based transformation projects. *Business process management journal*, *26*(7), 1893-1924. https://doi.org/10.1108/BPMJ-10-2019-0411

Wamba, S. F., Queiroz, M. M., & Trinchera, L. (2024). The role of artificial intelligence-enabled dynamic capability on environmental performance: The mediation

effect of a data-driven culture in France and the USA. *International Journal of Production Economics*, *268*, 109131. https://doi.org/10.1016/j.ijpe.2023.109131

Wang, S., & Zhang, H. (2024). Promoting sustainable development goals through generative artificial intelligence in the digital supply chain: Insights from Chinese tourism SMEs. *Sustainable Development*. https://doi.org/10.1002/sd.3152

Wong, L.-W., Tan, G. W.-H., Ooi, K.-B., Lin, B., & Dwivedi, Y. K. (2024). Artificial intelligence-driven risk management for enhancing supply chain agility: A deep-learning-based dual-stage PLS-SEM-ANN analysis. *International Journal of Production Research*, *62*(15), 5535-5555. https://doi.org/10.1080/00207543.2022.2063089

Wu, C. W., & Monfort, A. (2023). Role of artificial intelligence in marketing strategies and performance. *Psychology & Marketing*, *40*(3), 484-496. https://doi.org/10.1002/mar.21737

Xu, H., Niu, K., Lu, T., Li, S., & Lou, Q. (2024). Leveraging artificial intelligence for enhanced risk management in financial services: Current applications and future prospects. *Academic Journal of Sociology and Management*, *2*(5), 38-53. https://doi.org/10.5281/zenodo.13765819

Yu, H., & Guo, Y. (2023). Generative artificial intelligence empowers educational reform: current status, issues, and prospects. Frontiers in Education, 1183162. https://doi.org/10.3389/feduc.2023.1183162

Zahedi, M. H., Kashanaki, A. R., & Farahani, E. (2023). Risk management framework in Agile software development methodology. *International Journal of Electrical & Computer Engineering (2088-8708)*, *13*(4). https://doi.org/10.11591/ijece.v13i4.pp4379-4387

Zhan, X., Ling, Z., Xu, Z., Guo, L., & Zhuang, S. (2024). Driving efficiency and risk management in finance through AI and RPA. *Unique Endeavor in Business & Social Sciences*, *3*(1), 189-197. http://dx.doi.org/10.20944/preprints202407.0083.v1

Zhang, J., Liu, N., & Wang, S. (2021). Generative design and performance optimization of residential buildings based on parametric algorithm. *Energy and Buildings*, *244*, 111033. https://doi.org/10.1016/j.enbuild.2021.111033

Zhang, S., & Suntrayuth, S. (2024). The Synergy of Ambidextrous Leadership, Agility, and Entrepreneurial Orientation to Achieve Sustainable AI Product Innovation. *Sustainability*, *16*(10), 4248. https://doi.org/10.3390/su16104248