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Impact of supply chain integration and re-engineering on supply chain performance moderated by artificial intelligence in Qatar's public healthcare sector

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Supply chain resilience has rapidly expanded as a research area due to increased vulnerability to disruptions and uncertainties. Integration and re-engineering are essential components of a resilient supply chain that can improve its performance. Nevertheless, no one has yet investigated the effect of Artificial intelligence (AI) on the relationship between integration and re-engineering. Therefore, this study aims at investigating the roles of supply chain integration and re-engineering on supply chain performance. Similarly, it investigated the moderating role of AI in these relationships. This study develops a theoretical framework based on resource-based view and the social construction of technology theory. Based on a quantitative study of 564 responses collected from supply chain and clinical unit managers in the Qatari public healthcare sector, an empirical analysis was made using the partial least squares (PLS) path modelling technique. Results revealed that supply chain integration and re-engineering positively affect supply chain performance. Most significantly, these relationships are found to be positively moderated by AI. This study confirms the impact of supply chain integration and re-engineering on performance, providing empirical evidence for AI's role in strengthening these relationships.

1. Introduction

In today's complex business environment, global supply chains (SCs) face disruption risks due to short product life, unpredictability of demand, and varying customer expectations (Sangari & Dashtpeyma, 2019). Therefore, they are prioritizing strengthening their supply chain resilience (SCR) to enhance their capacity to manage such unforeseen disruptive events (Belhadi, Kamble, et al., 2021; Neboh et al., 2022). Businesses can mitigate SC disruptions by enhancing resilience enablers, particularly those impacting SCP, such as agility, integration, re-engineering, collaboration, velocity, visibility, flexibility, redundancy, coordination, and responsiveness (Agarwal et al., 2020). This study addresses supply chain integration (SCI) and supply chain re-engineering (SC Re-engineering). SCI is seen to be an organization's pillar in the face of intense market volatility (Piprani et al., 2020). It's described as the degree to which a company can strategically collaborate with its SC partners and cooperatively manage intra and inter-organizational processes to achieve effective and efficient flows with the objective of providing maximum value to its customers at low cost and high speed (Flynn et al., 2010). Sangari & Dashtpeyma (2019) argued that integration is a resilient element of the SC and other systems that resulted in long-term competitive advantage. According to Hammer & Champy (1993), SC re-engineering or Business Process Re-engineering (BPR) is defined as the fundamental questioning and radical redesign of organizational processes, to achieve dramatic improvements in current performance in cost, services, and speed. According to Tripathi & Gupta (2021), BPR is a method for assessing and re-engineering business processes with the goal of dramatically enhancing performance through the use of technology. Bahramnejad et al. (2015) claimed that BPR aims to make processes more competitive by improving quality, reducing expenses, and shortening the time needed to create a new product. Performance management, initially focused on business performance, then expanded to include various domains like lean manufacturing, logistics, and supply chain

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management (SCM) (Gopal & Thakkar, 2012). According to Som et al. (2019), Supply chain performance (SCP) is described as the operational outcomes of the company's SC functions following the implementation of different procedures. SCP is a major factor in determining an organization's success. It significantly depends on the adaptability and resiliency of SC partners in dynamic and unpredictable settings. It has a major impact on the business's ability to control expenses, deliver first-rate customer service, and react to various environmental threats (Riahi et al., 2021). Gunasekaran et al. (2001) claimed that SCM has been thoroughly examined in the past literature, However, little attention has been paid to SCP. This motivated Researchers to look at the potential influence of SCR in organizational performance, particularly during disruptions (Hejazi, 2021). Recently, AI has gained popularity as a research topic across many industries and businesses, including science, engineering, business, education, and healthcare. In SC context, AI is still an emerging technology with a lot of promise that we are yet to fully comprehend (AlSheibani et al., 2018). Riahi et al. (2021) argued that AI enables machines to perform tasks and make intelligent decisions without requiring human intervention. Further, AI offers enormous potential for SC risk analytics, which will enhance SCR. In addition, earlier studies suggested that utilizing AI as an analytics tool can improve SCP (Belhadi, Kamble, et al., 2021). AI adoption could improve the relationship between SCR and SCP, potentially impacting upstream and downstream stages of the SC (Riahi et al., 2021; Younis et al., 2021). However, previous AI research in the SC field is minimal and limited according to Younis et al. (2021) and (Belhadi, Kamble, et al., 2021). Hence, this study met the research objectives and closed the gaps in knowledge by exploring the impact of SCI and SC Re-engineering on SCP in Qatar's public healthcare sector, as well as examined the moderating roles of AI in these relationships.

2. Literature Review and Hypotheses Development

SC is an integrated process in which raw resources are turned into finished goods and subsequently distributed to clients (Beamon, 1999). SCP was defined by Tarafdar & Qrunfleh (2017) as the degree to which the SC satisfies end-customer expectations regarding product availability and timely delivery. Whereas Whitten et al. (2012) emphasized how important it is to guarantee customer satisfaction in terms of both cost and quality. SCM needs to assess its performance in order to create an effective and efficient SC (A. Gunasekaran et al., 2001). Previous research found that performance measurement systems are crucial in strategic, tactical, and operational planning, influencing objectives, performance assessment, and guiding future actions (Chorfi et al., 2018). Many businesses were unable to realize the full potential of their SCs. because they frequently failed to develop the performance measures and metrics needed to completely integrate their SCs (A. Gunasekaran et al., 2004). Others realized that performance measures significantly contribute to organizational success by evaluating and comparing results with peers' organizations (Taouab & Issor, 2019). Previous performance has been measured in different ways, including company performance, operational performance, and financial performance (Al-Doori, 2019). Further, previous scholars have suggested various measures for assessing SCP, but most are financial-related, such as profitability ratio and market value, which have been criticized for their limitations in evaluating actual organizational performance, especially in a rapidly changing market (Christopher & Peck, 2004; Abeysekara et al., 2019; Chorfi et al., 2018; Wu et al., 2014). Hervani et al. (2005) claimed that cost and a combination of cost and customer response have been the most used performance indicators in SC models. Whereas Angerhofer & Angelides (2006) and Wu et al. (2014) suggested three distinct performance measure types for ensuring overall performance success: resource measures, output measures, and flexibility. Resource describes how efficiently resources are managed inside a system to meet their goals. The goal of output is to measure product quality, timely delivery, and customer responsiveness. Flexibility is a system's capacity to handle changes in volume and schedule from manufacturers, suppliers, and customers.

In the healthcare setting, healthcare supply chains (HCSCs) play an important role in the industry's day-to-day operations (Rehman & Ali, 2021). HCSC does not have the choice of suspending operations as this might put human life at risk (Rehman & Ali, 2021). Improving HCSC performance is essential for enhancing operational efficiency and cutting costs as well as improving customer satisfaction in healthcare organizations (Mathur et al., 2018). This is due to the fact that HCSC is linked to high-cost medical supplies, equipment, and medications (Alotaibi & Mehmood, 2018). Nevertheless, this study examines SCP in terms of a healthcare organization's performance in managing its SC. It focuses on the operational aspect of SCP, integrating Tarafdar & Qrunfleh (2017) and Whitten et al. (2012) definitions to conceptualize SCP as a unidimensional construct.

Businesses can be distinguished based on their ability to reduce the severity and length of their SC disruptions due to their resilience. SCR can be a powerful strategic weapon in today's competitive market (Scholten et al., 2020). SCR helps SCs to guarantee the continuous delivery of their goods and services to customers even in turbulent circumstances. Belhadi, Kamble, Fosso Wamba, et al. (2021) refer to this ability as an enabler. Integration is a resilient factor in the SC that creates a competitive advantage. It enhances operational performance by improving information, cash flow, and service effectiveness. Firms utilize SCI to synchronize processes, coordinate, and share relevant information (C.-L. Liu & Lee, 2018). The COVID-19 pandemic highlighted the importance of SCI in healthcare, emphasizing the need for companies to adapt, develop sustainably, and build their SCR. SCI proved to improve a company's responsiveness to customer needs during the time of disruption (Siagian et al., 2021). Previous literature has extensively discussed the relationship between performance and integration. Lena (2021) argued that both agility and integration are capabilities of SCR that demonstrated a positive impact on operational performance. Siagian et al. (2021) argued that SCI can increase SCR by quickly adapting to unanticipated changes. Another study found that integrated IT infrastructures enhance organizations' higher-order capability of SC process integration, leading to improved firm performance (Rai et al., 2006). On the other hand, Zhuo et al. (2021) reported that no empirical data exists to support the link between resilience and integration of the food SC. Yu et al. (2018) found that there is no relationship between information exchange and integration from one side and financial performance from the other side.

SC re-engineering is the best tool to handle SC complexities and subsequently build SCR (Turhan & Vayvay, 2011). Earlier academics stressed that resilience should be built in. In other words, some features if engineered into a SC it will guarantee its resilience (Chen et al., 2013; Liu et al., 2018). Neboh et al. (2022) argued that re-engineering is a strategy that involves restructuring businesses, improving their efficiency, and reducing waste to enhance quality. Nabelsi & Gagnon (2015) highlighted the significance of incorporating risk management early in BPR in high-risk environments like healthcare. The relationship between SC Re-engineering and SCP has been examined by earlier researchers. Olajide & Okunbanjo (2020) revealed that all three components of BPR significantly enhance operational performance. Further, Yazdanparast et al.(2021) concluded that re-engineering, corporate social responsibility, dynamic assortment planning, flexibility, and decentralization as key enablers for enhancing the resiliency of a company and subsequently improving the performance. Similarly, Whitten et al. (2012) found that Triple-A supply chain strategy, including agility, adaptability, and alignment, positively impacts SCP, alignment described re-engineering. On the contrary, re-engineering has been found to have a negative impact on competitive advantage, and its relationship with performance remains unproven (Zepeda et al., 2016; Abeysekara et al., 2019). In addition, Clark & Hammond (1997), concluded that despite the widespread recognition of process re-engineering in business press, its empirical evidence shows minimal statistical significance.

This study addressed the inconsistency in past literature by empirically examining the relationship between SCI, SC Re-engineering, and SCP. This study is significant, especially because it targets Qatar, a country heavily reliant on imports due to limited local production capacity, and it focuses on the complex, unique HCSC (Al Naimi et al., 2021).

Wernerfelt (1984) initially proposed the Resource -Based View (RBV) theory, arguing a firm's performance is influenced by both direct and indirect resources used in production. Later, the paper published by J. Barney (1991) was widely considered as the first comprehensive and empirically tested theoretical framework for the fragmented resource-based literature. The RBV theory argues that businesses with scarce, valuable, non-imitable, and non-substitutable resources outperform others (Barney, 1991). Based on this notion, this research made its argument that SCI and SC Re-engineering are the main resources that the SC needs to grow and preserve. Which will eventually result in SCR, and the achievement of sustained SCP. Thus, we postulate that:

H$_1$: *SCI has a positive and significant relationship with SCP.*
H$_2$: *SC Re-engineering has a positive and significant relationship with SCP.*

AI, a set of tools and algorithms, mimics human thinking, providing a framework for informed decision-making. It can be categorized into rational thinking, rational acting, human thinking, and human acting techniques (Belhadi, Kamble, et al., 2021). AI adoption enhances businesses' competitive advantage by improving projection accuracy, cost efficiency, and customer experience (Naz et al., 2021; Dixit et al., 2019). Recent literature emphasizes the importance of technology in establishing SCR for adaptive systems. AI techniques are expected to develop these capabilities (Belhadi, Kamble, et al., 2021). The COVID-19 pandemic has led to more businesses adopting technology for SCM and mapping, with over half (55.6 percent) using it for analysis and reporting on disruptions as documented in the SCR report issued by BCI (2021). In reality AI is among the most remarkable technologies that could contribute to the improvement of SC's capabilities and, consequently, its transformation (Riahi et al., 2021). In addition, Naz et al. (2021) argued that AI's short-term impact on SCR is significant, with its information analysis being a key factor. Furthermore, according to Modgil et al. (2022), SCs and organizations failing to utilize AI may struggle to achieve essential SCR in COVID-19-like situations.

Past literature elaborated on the relationship between AI, SCI, and SC Re-engineering. In his study, Benzidia et al. (2021) revealed that implementing BDA-AI technology greatly influences green SC collaboration and environmental process integration. Shukor et al. (2021), added that their research enhances the impact of Industry 4.0 adoption on Malaysia's services and manufacturing industry, enhancing SCI, agility, and organizational flexibility. Furthermore, Belhadi, Kamble, Fosso Wamba, et al. (2021) found that rational action and thinking techniques had the biggest impacts on SC re-engineering. Likewise, Huang et al. (2015) asserted a positive correlation between employee performance and the implementation of BPR and IT.

Previous studies in several domains, including the humanitarian SC (Dubey et al., 2021), circular SC (Del Giudice et al., 2020), and hotel business (Nguyen & Malik, 2022) have established the impact of AI's moderation. This study, however, closes a gap in the literature by being among the first to examine the role AI moderation plays in the relationships between SCI, SC Re-engineering, and SCP. The Social Construction of Technology (SCOT) theory, introduced by T. J. Pinch & Bijker (1984), views technology as a force in social change and innovation. According to the SCOT theory, human behavior shapes technology rather than technology determining human behavior. In addition, employees adopt technology to accomplish human objectives, enhance society, and further personal interests T. J. Pinch & Bijker (1984). Consequently, several businesses have adopted AI. Thus, we postulate that:

H3: *AI moderates the relationship between SCI and SCP.*
H4: *AI moderates the relationship between SC Re-engineering and SCP.*

The theoretical framework of this study is illustrated in **Fig. 1.**

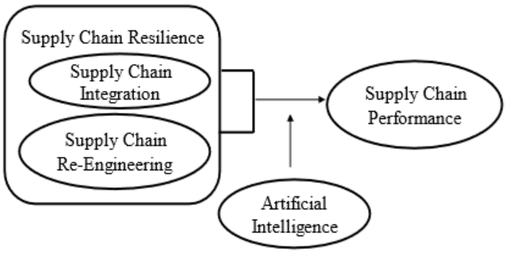

Fig. 1. Theoretical Framework

3. Material and Methods

3.1 Variable Measurements

This study is quantitative in nature adopting a cross-sectional design, which is the most convenient technique for this study since it is utilized to investigate established study objectives and hypotheses over a specific period of time (Zikmund et al., 2010). This empirical study explored the correlation between SCI, SC Re-engineering, and SCP, and the moderating role of AI in these relationships. This study employed an online survey questionnaire for data collection adopting a five-point Likert scale (1= strongly disagree to 5= strongly agree) to measure respondents' opinions. Business and management scholars frequently use this survey approach to effectively gather a lot of data from a big population (Saunders et al., 2009; Zikmund et al., 2010).

In this study, SCI and SC Re-engineering are employed as the independent variables, SCP as a dependent variable, and AI as a moderator. All constructs' items used in this study were adapted from past studies. SCI is measured using ten items adapted from, C. L. Liu & Lee (2018) and C. L. Liu et al. (2018), SC Re-engineering is measured using nine items adapted from Olajide & Okunbanjo (2020) and Abeysekara et al. (2019), SCP is measured using ten items adapted from Tarafdar & Qrunfleh (2017) and Angappa Gunasekaran et al. (2017), and AI is measured using ten items adapted from Wixom & Todd (2005) and Belhadi, Mani, et al. (2021). To ensure validity and reliability of this study, a pretest was carried out involving a total of 35 participants, which were identical to the targeted respondents. Factor loadings, construct reliability, and validity were all found acceptable.

3.2 Sampling Design and Data Collection

This study examines the moderation role of AI adoption on the relationship between supply chain resilience and performance in the Qatari public healthcare sector, focusing on middle and top-level managers experienced in SC practices and new emerging technologies employed in Hamad Medical Corporation (HMC)and Primary Health Care Corporation (PHCC).

Data collection for this study lasted for seventy-five (75) days, from October 1st, until December 15th, 2023. A self-administered online survey questionnaire was emailed to 1605 randomly selected participants who were taken out of the study sample frame. The questionnaires were provided with a cover letter, ensuring confidentiality for academic purposes, and clearly outlining study objectives, with multiple reminders to boost participation and response rates. Moreover, this study uses stratified sampling design to ensure the best population representation and a minimum sample size of 155, using inverse square root method with a common power level of 80 percent, a significance level of 5 percent, and a minimum path coefficient of 0.2(Hair et al., 2021; Kock & Hadaya, 2018). The study received 607 responses, with a 37.8% response rate. 31 were disregarded due to incomplete responses (50% of items were left unanswered) (Hair et al., 2021). 12 were removed due to non-response bias (SD less than 0.25) (Collier, 2020). 564 valid responses were used representing 35.14 % response rate. All data were coded using IBM Statistical Package for Social Sciences version 28.

4. Research Results

4.1 Demographic Profile of Respondents

In terms of sample characteristics, the results showed that 54.8% of respondents were male and 45.2% were female, most of them aged between 34 and 49, with a majority (81.8%) working in clinical manager/executive roles compared with 18.6% working in supply chain manager/executive roles. The vast majority of respondents (86.9%) work for HMC, while only 13.1%

work for PHCC, which matches the size of both corporations. The majority of respondents (32.8%) had more than 15 years of managerial experience. Lastly, most respondents (56.7%) worked in tertiary-level healthcare facilities, compared with 24.1% working in secondary facilities and 18.3% doing so for primary healthcare facilities.

4.2 Partial Least Squares Path Modelling (PLS-PM)

Structural Equation Model (SEM) is a statistical technique that examines correlations between independent and dependent variables. It models and estimates complex interactions, allowing for measurement error in observable variables (Ullman & Bentler, 2012). PLS is a regression-based SEM technique used for analyzing high-dimensional data in low-structure settings, assisting in model calculation, validation, and application of predictive measures in management science (Hair et al., 2021; Sander, 2014). The PLS path model consists of two linear equations: a structural model, which describes relationships between unobserved or latent variables, and a measurement model, which describes relationships between latent variables and their observed ones (Hair et al., 2021). Initially, this study examined common method bias (CMB), which has been noted as an important concern in self-reporting surveys where participants read and select their own responses without the researcher's intervention. The single factor test by Harman is used to assess CMB. According to Podsakoff et al. (2003), the study revealed that a single-factor solution explained 30.22% of the total variance, which is less than the 50% threshold therefore not a significant concern. Further, the proposed model was tested using SmartPLS 4.0 software and examined both measurement and structural models in line with the established recommendations of (Hair et al., 2021).

4.2.1 Measurement Model Analysis

We evaluated the validity and reliability of the measurement model used in this study. All indicators, as shown in Table 1, have an outer loading of 0.70 or greater, indicating their reliability in accordance with recommendations from Joseph F. Hair et al. (2021).

Table 1
Summary of Outer Loadings Results

Construct	Item	Loadings
Supply Chain Integration (SCI)	SCI1	0.813
	SCI2	0.854
	SCI3	0.875
	SCI4	0.869
	SCI5	0.869
	SCI6	0.871
	SCI7	0.884
	SCI8	0.873
	SCI9	0.876
	SCI10	0.884
Supply Chain Re-engineering (SCREEN)	SCREEN1	0.809
	SCREEN2	0.850
	SCREEN3	0.874
	SCREEN4	0.878
	SCREEN5	0.874
	SCREEN6	0.867
	SCREEN7	0.859
	SCREEN8	0.860
	SCREEN9	0.854
Artificial Intelligence (AI)	AI1	0.712
	AI2	0.757
	AI3	0.739
	AI4	0.695
	AI5	0.735
	AI6	0.711
	AI7	0.725
	AI8	0.687
	AI9	0.732
	AI10	0.690
Supply Chain Performance (SCP)	SCP1	0.797
	SCP2	0.848
	SCP3	0.852
	SCP4	0.867
	SCP5	0.863
	SCP6	0.871
	SCP7	0.878
	SCP8	0.872
	SCP9	0.882
	SCP10	0.886

Furthermore, as shown in Table 2, composite reliability and Cronbach's alpha of latent constructs are all above 0.90, indicating sufficient internal consistency reliability. Using the Heterotrait-Monotrait Ratio (HTMT) and Average Variance Extracted (AVE) methods, convergent and discriminant validity were assessed. All of the AVE values in this research were higher than the 0.50 cutoff, indicating adequate convergent validity (see Table 2). Likewise, as shown in Table 3, the HTMT ratio values are also all less than 0.90, suggesting that the criterion for discriminant validity is appropriate.

Table 2
Summary of Cronbach's alpha, composite reliability (rho_c), and AVE results.

Construct	Cronbach's alpha	Composite reliability (rho_c)	AVE
Supply Chain Integration	0.964	0.968	0.752
Supply Chain Re-engineering	0.956	0.962	0.737
Artificial Intelligence.	0.896	0.914	0.516
Supply chain performance.	0.961	0.967	0.743

Table 3
Discriminant Validity (HTMT) Results.

Construct	SCI	SCREEN	AI	SCP
Supply Chain Integration (SCI).				
Supply Chain Re-engineering (SCREEN).	0.174			
Artificial Intelligence (AI).	0.611	0.606		
Supply chain performance (SCP).	0.327	0.360	0.764	

4.2.2 Structural Model Assessment

The structural model evaluation involves three phases: assessing potential collinearity between predictor constructs, examining the significance and applicability of path coefficients, and analyzing the model's explanatory and predictive power (Hair et al., 2021). The study assessed research hypotheses using path coefficients(ß), standard error (SE), t-value (T Statistics), and p-value, which indicates the significance levels (< 0.05= significant) as shown in Table 4. Based on the positive relationships between SCI and SCP (ß = 0.367, T = 10.218, P = 0.000) and SCREEN and SCP (ß = 0.327, T = 9.164, P = 0.000), H1 and H2 are supported. Moreover, the moderation effect of AI on the relationships between SCI and SCP (ß = 0.116, T = 3.858, P = 0.000) and SCREEN and SCP (ß = 0.104, T = 3.872, P = 0.000) was found to support the hypotheses H3 and H4. Remarkably, the framework explained 62.8% of the variance (R^2), attributed to SCI, SCREEN, AI, and AI interaction. Nevertheless, the predictive relevance demonstrated by the PLS prediction technique for this research was greater than zero, with a Q^2 value of 0.551.

Tabel 4
Structural Model: Test of Significance for Direct and Indirect (Moderation) Relationships

Hypothesis	Relationship	Path coefficient (ß)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P Values	Decision
H1	SCI → SCP	0.367	0.036	10.218	0.000	Supported
H2	SCREEN → SCP	0.327	0.036	9.164	0.000	Supported
H3	AI × SCI → SCP	0.116	0.030	3.858	0.000	Supported
H4	AI × SCREEN → SCP	0.104	0.027	3.872	0.000	Supported

Significance level: P<0.05 (n=564)

4.2.3 Moderation Analysis

The study also conducted simple slope plots analysis to better understand the relationship between SCI, SC RE-engineering, and SCP at different AI moderation levels. Results showed a positive correlation between SCI, SC Re-engineering (SCREEN) and SCP, with a steeper relationship at high AI (+1 SD).

5. Discussion

The relationship between SCI and SCP was examined and found significant. This result of supported H1 indicate that SCI positively affects SCP among SC and clinical unit managers within Qatar's HCSC.These results align with earlier studies that looked at this relationship in various settings (Espino-Rodríguez & Taha, 2022; Koçoğlu et al., 2011; Lena, 2021; C.-L. Liu & Lee, 2018). These findings suggest that public healthcare organizations in Qatar can significantly improve performance by promoting high levels of SCI. It also indicates that SCI facilitates coordination, integration of tasks, information sharing, and strong linkages with customers and suppliers, optimizing resource deployment and utilization. Additionally, managers and decision makers view the improved operational efficiencies and lower costs are key factors influencing SCP in the healthcare industry. With its foundation in RBV theory, this study emphasizes the strategic importance of SCI as a rare, and inimitable asset, which comprises high coordination, rapid information transmission, and process synchronization across HCSC components that result in improved SCP.

Furthermore, the study found a significant positive impact of SC Re-engineering on SCP (ß = 0.327, T=9.164, P=0.000), supporting the hypothesis that SC Re-engineering influences SCP (H2). This aligns with previous research indicating a positive correlation between performance and business process re-engineering, promoting resilience and competitiveness in SCs (Bahramnejad et al., 2015; Huang et al., 2015; C.-L. Liu et al., 2018; Neboh et al., 2022; Whitten et al., 2012).

From this study's findings, it can be concluded that SC members and managers in Qatari public healthcare organizations can improve SCP by analyzing and redesigning processes, reallocating resources, and having reliable backup utilities. Grounded in RBV theory, this outcome also emphasizes the importance of SC re-engineering as a strategic, valuable, and inimitable capability for transforming SC into a flexible, adaptable system for the healthcare industry.

More importantly, the results of hypothesis testing analysis revealed that AI has a positive significant moderation effect on the relationship between SCI, and SC R-engineering and their impact on SCP. Hence, H3 and H4 were supported. This finding is in lieu with results from past literature that demonstrated AI moderation in other contexts, in the hotel sector Prentice et al. (2020a,b) assert that while AI moderates employee performance, emotional intelligence significantly impacts staff retention and performance. Narayanamurthy & Tortorella (2021) discovered that 4.0 technologies can moderate the correlation between COVID-19's work implications and employee performance. This study's results are also similar to previous research by Nguyen & Malik (2021) Dubey, Bryde, et al. (2021) Del Giudice et al. (2020).

Based on the SCOT theory, the study's results show how important AI is as a moderator in improving SCI and SC re-engineering effectiveness in order to achieve higher SCP. Such findings suggest that healthcare managers adopt AI-powered tools for automated decision-making, predictive analytics, and real-time data exchange in order to achieve a high degree of SCI, which will enhance SCP and, thus, improve patient care outcomes. It also suggests that AI tools can help managers and staff lower the cost of healthcare services, boost output, increase efficiency, streamline SC processes, and subsequently improve SCP in healthcare organizations.

6. Research implications

This study has several theoretical and practical implications that are elaborated below.

6.1 Theoretical Implications

The study offers scholars some significant theoretical implications. This study advances the RBV and SCOT theories to explain Qatar's HCSC performance from a SCR perspective, considering AI adoption's moderation role. It added to the body of knowledge by presenting empirical evidence for the moderating influence of AI on the link between SCI and SC Re engineering as SCR enablers and SCP in the public healthcare sector in Qatar. The study also provides empirical proof that SCI and SCR-engineering practices positively affect SCP in Qatar, under unique circumstances where its medical SC relies heavily on imports due to limited local production capacity and recent blockade implications.

6.2 Practical Implications

Concerning the practical implications. This study motivates managers to enhance their competencies, such as integration and re-engineering, to gain a competitive advantage for SCP promotion within HCSC. It also encourages healthcare managers and other stakeholders to significantly invest in AI-related technology to enhance their SCP. In addition, policymakers are encouraged to adopt localized supply chains to boost growth, attract foreign investors, and enhance the business environment.

7. Conclusions, Limitations and Future Research

In conclusion, this study investigates the influence of SCI and SC Re-engineering on SCP in Qatari public healthcare institutions. More importantly, the study also looked at how AI might moderate these correlations. Based on data analysis, it is concluded that SCI and SC Re-engineering significantly impact SCP. Similarly, it was found that AI had a positively significant moderating influence on these interactions. Although this study has made significant contributions, it is crucial to acknowledge some limitations. First, the online survey was the only instrument used in this quantitative research which is influenced by respondents' education and cooperation levels, Future studies can overcome this limitation by utilizing mixed methods of research, which combines qualitative and quantitative techniques. Second, because this study only looked at SCI and SC Re-engineering, more research is needed to expand this analysis in HCSC by considering other crucial SCR enablers into account. Third, SCP, the dependent variable in this study, was conceptualized as operational non-financial performance; however, financial performance metrics could be taken into consideration in future research to better understand and evaluate SCP. Finally, the study, limited in generalizability, because it primarily examined the healthcare industry in Qatar, future research therefore should expand its scope to encompass other GCC countries.

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