ORIGINAL ARTICLE

Generative AI and its impact on Supply Chain Performance in Faisalabad health care system.

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Article History:

Submitted: May 10, 2025
Revised: April 22, 2025
Accepted: March 19, 2025
Published online: June 30, 2025

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ABSTRACT

Traditionally, investigation on Artificial Intelligence mainly dedicated on its implications, including the advantages and disadvantages of its application. However, investigating the factors driving the demand for AI across various domains is equally critical, particularly for stakeholders and employees striving to enhance their efforts and organizational growth. This issue holds significant relevance for Pakistan, especially given the recent decline in the country's economic performance. A noticeable trend in Pakistan is the preference for manual methods over technological solutions. The objective of this study is to explain the key factors influencing artificial intelligence adoption among the people of Pakistan, with a particular focus on the healthcare sector. Data was gathered from 108 valid health care respondents, and the proposed research model was evaluated using regression analysis through PLS-SEM software. Hypotheses were subsequently tested. The findings indicate that artificial intelligent overall impact is positive, even when mediated by factors such as production management, supplier collaborations and relationships, and a digital and intelligent environment. These results provide valuable insights for policymakers, emphasizing the need to incorporate AI into routine activities and encourage its use among employees. Initiatives like employee training and development programs to highlight AI's benefits and enhance their expertise in specialized areas would significantly contribute to skills improvement and overall productivity.

Keywords: Electronic Supply Chain System, Supply Management, Integrating Digital Technologies, Generative AI, Manufacturing Processes, Resource availability, and Demand, Collaboration.

1 | INTRODUCTION

In today's fast-paced global market, procurement and supply chain management play a pivotal role in determining an organization's competitive edge and overall performance (Brown, 2020). These functions are essential for efficiently sourcing resources, managing costs, and ensuring the smooth flow of goods and services from suppliers to end consumers (Brown, 2020). As technological advancements continue to reshape business operations, one of the most significant innovations is Generative Artificial Intelligence (AI) (Brown, 2020).

Generative AI, which is capable of creating content, simulating human thought processes, and solving complex problems, has moved beyond the realm of science fiction to become a powerful tool for businesses. By leveraging machine learning and neural networks, models like GPT-3 and its successors have captured widespread attention from both technology experts and business leaders. The ability of these AI systems to comprehend and produce language that is similar to that of humans has created new opportunities, especially in the supply chain management and procurement fields (Radford, 2019).

Generative AI's incorporation into supply chain and procurement operations represents a significant change in how these processes are carried out, not just a technical advancement. Generative AI is revolutionizing tactics and operations in a variety of fields, from automating monotonous chores to improving decision-making through sophisticated data analysis.

This study examines how supply chain management and procurement are being transformed by generative AI. It examines how companies are presently implementing these technologies to boost supply chain transparency, reduce expenses, and increase efficiency. It also covers the difficulties and moral dilemmas associated with applying generative AI in various fields.

Organizations hoping to prosper in the digital era must comprehend how generative AI can transform supply chain management and procurement in a cutthroat market where technology plays a critical role in success. This research offers a thorough examination of the existing and upcoming effects of generative AI, highlight

1.1 | Background of the Study

The healthcare industry is not an exception to how the incorporation of cutting-edge technologies has drastically changed businesses throughout the world in recent years. The importance of technology innovation in healthcare has increased due to the crucial nature of hospital operations, which require maximum efficiency and few mistakes (Radford, 2019). Adoption of innovative technology is essential as hospitals seek to improve patient care outcomes, lower costs, and increase operational efficiency (Kuo, 2017). Generative Artificial Intelligence (Generative AI) is one such innovative technology that has the potential to completely transform healthcare supply chain operations.

The purchasing, storing, and distributing of medical supplies, medications, and equipment needed for patient care are all part of the intricate healthcare supply chain. The effectiveness of this supply chain is critical due to the high stakes involved in healthcare operations. Its objective is to guarantee the prompt and sufficient provision of essential healthcare services. With its strengths in natural language processing and machine learning, generative AI has promise for improving the healthcare supply chain's responsiveness, accuracy, and efficiency in a number of areas.

This study is to investigate the application of generative artificial intelligence (AI) in hospital supply chains and evaluate its impact on important performance metrics including inventory control, cost reduction, and overall operational effectiveness. To make wise judgements on its integration, hospital executives, legislators, and tech developers must have a thorough understanding of how generative AI impacts healthcare supply chains.

As AI technologies become more integrated into healthcare systems, ethical and regulatory concerns also grow in importance. It is critical to address the ethical challenges associated with Generative AI in hospital supply chains, particularly those related to data privacy, algorithmic bias, and transparency. Exploring these issues will ensure that the adoption of this technology aligns with ethical standards and complies with relevant regulations.

1.2 | Problem Statement

The rapid advancements in technology are transforming every industry, and the healthcare and medical sectors are no exception. These fields are actively adapting to technological progress, with the application of Generative AI gaining significant attention in recent years. Generative AI has demonstrated its utility across various aspects of healthcare, including medical imaging, clinical documentation, diagnostic interpretation and molecular modeling (Shokrollahi, 2022).

Despite the progress made, there is still a significant lack of research focusing on how Generative AI influences the performance of hospital supply chains. Effective supply chain management in healthcare is crucial to ensure that medical products are delivered promptly, accurately, and cost-effectively (Kuo, 2017).Effective supply chain performance is critical for the seamless operation of hospitals and their ability to meet patient needs.

This study aims to explore the influence of Generative AI on hospital supply chain performance. It seeks to examine how Generative AI can optimize procurement processes and reduce costs within hospital supply chains, as highlighted in discussions with healthcare representatives. By investigating these areas, the study aims to provide valuable insights into the potential of Generative AI to enhance hospital supply chain efficiency and overall performance.

1.3 | Objectives OF THE STUDY

a) Assess the potential applications of Generative AI in optimizing various aspects of the supply chain, such as demand forecasting, inventory management, and procurement.
b) Evaluate the impact of Generative AI on supply chain performance metrics, including cost reduction, inventory turnover, order fulfillment, and customer satisfaction.
c) Provide recommendations and guidelines for healthcare organizations on effectively implementing Generative AI solutions to enhance supply chain performance, considering factors like organizational readiness, change management, and stakeholder engagement.

1.4 |Questions OF THE STUDY

1. RQ1: How does Artificial Intelligence (AI) influence Supply Chain Processes (SCP) in healthcare settings in Faisalabad, and what is the strength of this connection?

2. RQ2: What impact does Supplier Collaboration and Relationship (SCR) have upon the relation between Supply Chain Processes (SCP) and Artificial Intelligence (AI) in the healthcare industry of Faisalabad?
3. RQ3: How do production management strategies enhance Supply Chain Performance (SCP) through the application of Artificial Intelligence (AI) in healthcare organizations in Faisalabad?
4. RQ4: How does the Digital and Intelligent Environment play a role in shaping the impact of Artificial Intelligence (AI) on sustainable supply chain performance in Faisalabad's healthcare industry?

2 | LITERATURE REVIEW

2.1 | Generative Artificial Intelligence (AI)

Artificial Intelligence (AI) refers to technologies designed to simulate human cognitive abilities, such as thinking, learning, adaptation, interaction, and sensory perception (Scott D. Tagliaferri, 2020; Yanmin Li, 2022; Study, 2019). Over recent decades, AI and robotics have significantly advanced in areas like medical assistance and scientific discovery (Trishan Panch, 2018). The rise of big data, along with improvements in modeling techniques and computational power, has led to a more data-driven approach to healthcare and disease prevention. AI is now crucial in analyzing therapeutic data, self-monitoring, and using patient and claim information to recommend treatments and improve outcomes (Trishan Panch, 2018). Some systems are even capable of performing tasks that typically require human judgment and decision-making (Trishan Panch, 2018). AI's interdisciplinary applications extend beyond healthcare, influencing various fields, including medicine, where it has been utilized since the 1950s to enhance diagnostic accuracy through computer-aided programs (Xin Yang, 2019).

AI has evolved significantly over the last century, especially with the advent of Industry 4.0 technologies. Its development has continued from its roots in the 1950s, when mathematician Alan Turing pioneered early concepts of machine intelligence (Solomonoff, 1985). The formal emergence of AI as a field began in 1956 with the Dartmouth Summer Study Group. AI is commonly defined as the creation of intelligent systems that can understand, process, interpret, and make decisions and predictions, making it one of the most influential technologies of Industry 4.0. Christopher Collins, 2021, Min, Seo, Lee, Park, & Hong (2010) states that the objective is to create "thinking machines" that can mimic, learn, and even outsmart humans. AI, according to Marvin Lee Minsky (1956), is the creation of computer programs that carry out operations that normally call for human brain functions, such reasoning, memory organisation, and perceptual learning. According to Bringsjord and Schimanski (2003), intelligence is the capacity of an agent to perform exceptionally well on all recognised and verified intelligence tests.

A network of artificial neurones called an artificial neural network (ANN) is made to resemble the way the human brain perceives and processes information. This allows the ANN to tackle complicated issues that are normally difficult for people to handle. The nodes that make up an ANN are connected to one another through connections. The network uses internal weights to interpret "input" data and produce "outputs" using a set of learning rules. ANNs are able to continually improve their performance because to this self-learning process.

A mathematical method for dealing with imprecise, ambiguous, or noisy data is called rough set theory. In order to better characterise data sets and depict an ambiguous idea, it establishes two bounds, known as the lower and higher approximations.

Machine Learning (ML) refers to a process that enables systems to learn and improve from experience without explicit programming, relying on past data to refine performance (Ke-Lun He a, 2019). Common types of ML include: 1) supervised learning, which focuses on classification and regression tasks, 2) unsupervised learning, which deals with tasks like association rules, self-organizing maps, and dimensionality reduction, and 3) reinforcement learning, where systems autonomously find solutions through rewards and penalties (Ke-Lun He a, 2019). An Expert System is designed to provide solutions or answers to problems by reasoning with known facts and rules, often serving as a decision support tool. Genetic Algorithms (GAs) are optimization techniques inspired by the principles of natural selection. These algorithms solve complex problems by exchanging information randomly to explore solutions (Ke-Lun He a, 2019).

Fuzzy logic extends Boolean logic by incorporating the mathematical theory of fuzzy sets, offering a broader interpretation of classical set theory. Unlike traditional logic, which typically classifies conditions as true or false, fuzzy logic introduces the concept of a degree of truth, allowing conditions to exist in varying levels. This flexibility makes it possible to address situations with uncertainty or imprecision (Killeen, 2014).

An agent-based system consists of a group of agents—such as processes, robots, or humans—operating within a specific environment and interacting based on set rules (Toorajipour, 2021). An agent is distinguished by its partial autonomy, meaning it can function independently to some extent (Toorajipour, 2021). Data mining, case-based reasoning, swarm intelligence, support vector machines, simulated annealing, automated planning, decision trees, association rules, tree-based models, hill climbing, k-means clustering, expert systems, heuristics, robot programming, stochastic simulation, Bayesian networks, Physarum models, rule-based reasoning, and Gaussian models are some more general AI approaches that are also used in supply chains, albeit less frequently (Toorajipour, 2021).

2.2 | Supplier Collaboration and Relationship

Working together with suppliers is essential to generative AI's successful supply chain integration. Research indicates that strong collaboration with suppliers enhances data sharing, a key requirement for training generative AI models (P. J. Standen, 2021). Organisations may collect broad and precise datasets through strong collaborations, which helps to create AI systems that are more dependable and effective.

Studies also highlight that Green Supply Chain Collaboration (GSCC) has a significant positive impact on the environmental performance of hospitals (Smail Benzidia, 2021). Hospitals that engage closely with their suppliers tend to achieve superior green outcomes. This aligns with theories suggesting that adopting collaborative strategies helps organizations maintain supplier relationships and enhance environmental performance (EP) (Stephan Vachon, 2008; Abdul-Nasser El-Kassar, 2019). However, the hospital sector often faces challenges due to a lack of capacity and maturity in implementing environmental practices, making supply chain collaboration a critical process.

In the context of a circular economy, GSCC involves the collaboration between companies and their suppliers to improve green decision-making and outcomes. This includes designing eco-friendly products, managing sustainable supply, production, recycling, and waste management throughout the lifecycle of materials and components (Junjun Liu, 2018). Collaboration within the supply chain remains a significant challenge, as achieving sustainable results requires active involvement from all members (Kamble et al. & Centobelli et al., 2020). Supply chain development can be further enhanced when suppliers adopt environmentally friendly practices that align with client demands (Abdul-Nasser El-Kassar, 2019).

Existing literature underscores the link between internal environmental integration and supplier collaboration as crucial for achieving sustainable environmental performance (EP) (Abdul-Nasser El-Kassar, 2012). Although this relationship is extensively explored in broader contexts, there is a noticeable gap in studies focusing on its application within the hospital sector.

2.3 | Digital and Intelligent Environment

Using artificial intelligence (AI) technology like machine learning and deep learning, intelligent supply chain management is a state-of-the-art method of monitoring the movement of products and services. This cutting-edge solution optimises inventory management, lowers expenses, increases customer happiness, increases process efficiency, and improves decision-making accuracy (Brown, 2020).

The implementation process begins with identifying specific business needs that can be addressed through AI. Once these requirements are determined, they are matched with suitable AI solutions, such as natural language processing (NLP), robotic automation, or predictive analytics.

Selecting an appropriate AI platform or vendor is the next critical step. This selection should consider the provider's capabilities, industry expertise, and customer feedback. After selecting a vendor, the AI system must be integrated with existing infrastructure, including ERP software and supply chain management tools.

One significant advantage of digitizing supply chains is the ability to gain real-time visibility into logistics, such as inventory levels. Real-time insights help companies maintain optimal stock levels, enabling them to meet fluctuations in consumer demand without overstocking or wasting resources (Collins, 2021).

Smart technologies combined with big data analytics can further enhance sustainability in product design. For instance, Hamed Gholami (2017) developed a decision-support system that measures greenhouse gas emissions and carbon footprints during supplier selection. This system integrates big data analytics, cloud computing, and operational research methods, including AHP, DEMATEL, and TOPSIS, to support environmentally conscious decision-making.

2.4 | Production Management

By combining optimization, predictive modelling, and sophisticated analytics, artificial intelligence is completely changing traditional production management. Businesses may handle vast amounts of data from various sources by using AI algorithms, which facilitates real-time decision-making and increases overall operational efficiency (Alcácer, 2022).

Effective production planning relies heavily on accurate demand forecasting, where AI methods, particularly machine learning, have shown significant effectiveness (Gurupad,2022). AI has also found widespread application in production scheduling, helping to streamline the management of complex production environments. For instance, Gallo (2023) introduced a smart production scheduling framework that applies AI algorithms to optimize production plans, factoring in various constraints and uncertainties. The research demonstrated that AI-driven scheduling notably enhanced production efficiency and shortened lead times.

2.5 | Supply Chain Process

Supply Chain Management (SCM) is a network of interconnected facilities that source raw materials, convert them into intermediate or finished goods, and deliver these products to customers via a distribution system. SCM encompasses procurement, manufacturing, and distribution activities (Billington, 1995). The primary goal of supply chain management is to "optimize the chain's performance to deliver maximum value at the lowest possible cost." In essence, SCM seeks to align all supply chain participants to work collaboratively within an organization to enhance productivity and maximize benefits for all stakeholders involved (Gurupad, 2022).

Since the 1980s, the adoption of supply chain management practices across industries has grown steadily. Numerous definitions and perspectives on SCM have been proposed over time. For instance, Shukla (2011) provided a comprehensive review of the literature on supply chain management, defining its concepts, principles, nature, and evolution. These studies highlight the significant progress in SCM research globally, critically examining developments in both theory and practice.

2.6 | Enablers of AI and Supply Chain Processes

The term "enabler" refers to a company's actions that serve as the driving force or catalyst for adopting AI and its associated tools (Latifa Al Zarooni, 2023). These enablers often arise from the company's established practices and expertise in implementing AI (Latifa Al Zarooni, 2023). This phase involved conducting a literature review to identify the factors that facilitate AI adoption and its impact on the healthcare sector. To manage the existing information, we employed the PRISMA method, as shown in Figure 1, which outlines the number of articles retrieved and the ones selected for further analysis. Several articles were excluded due to their lack of relevance to the core theme of our study.

2.7 | Hypothesis Development

Prior studies by Leong Chan-Hoong and Debbie Soon (2010) and Speelman et al. (2017) in the Maldives have shown a strong correlation between the dependent variable, Supply Chain Processes (SCP), and each of the independent variables: Production Management (PM), Digital and Intelligent Environment (DIE), Supplier Collaboration and Relationships (SCR), and Artificial Intelligence (AI). The following theories, which centre on the Pakistani setting, have been established based on these earlier findings. The hypothesis are as follows:

1. Artificial Intelligence (AI) positively affects the Supplier Collaboration and Relationships (SCR).
2. Artificial Intelligence (AI) positively affects the Digital and Intelligent Environment (DIE).
3. Artificial Intelligence (AI) positively affects the Production Management (PM).
4. Supplier Collaboration and Relationships (SCR) positively affects Supply Chain Processes (SCP).
5. Digital and Intelligent Environment (DIE) positively affects Supply Chain Processes (SCP).
6. Production Management (PM) positively affects Supply Chain Processes (SCP).
7. Supplier Collaboration and Relationships (SCR) mediates the relation between Artificial Intelligence (AI) and Supply Chain Processes (SCP).
8. Digital and Intelligent Environment (DIE) mediates the relation between Artificial Intelligence (AI) and Supply Chain Processes (SCP).
9. Production Management (PM) mediates the relation between Artificial Intelligence (AI) and Supply Chain Processes (SCP).

2.8 | Conceptual Framework

The conceptual framework for this study, based on Resource-Based Theory (RBV), is presented in Figure 1. While the resource-based view of the firm has become a dominant perspective in strategic management, its impact on organizational theory has been relatively limited. According to RBV, organizations achieve competitive advantage by effectively utilizing valuable, rare, inimitable, and non-substitutable (VRIN) resources. In the context of hospital supply chain performance (SCP), the model proposes that Artificial Intelligence (AI) acts as a strategic resource that enhances critical capabilities such as Supplier Collaboration and Relationships (SCR), the Digital and Intelligent Environment (DIE), and Production Management (PM)—all of which are instrumental in improving SCP.

The hypotheses and visual model suggest a direct and mediated influence of AI on SCP through these three mediators, aligning with RBV's emphasis on internal resource development. By leveraging AI as a dynamic and transformative capability, hospitals can enhance operational efficiencies, responsiveness, and innovation across the supply chain. This model, therefore, not only captures the strategic application of AI in healthcare logistics but also reflects RBV's assertion that organizational performance is contingent upon the effective deployment and integration of key resources.As a result, hypotheses have been formulated to provide a foundation for further investigation and analysis in this study.

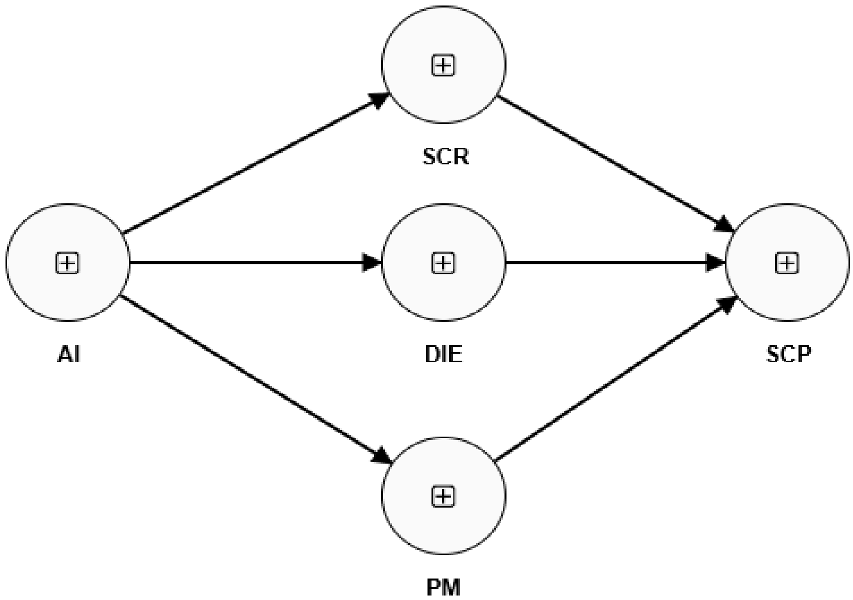

Figure 1 Conceptual Framework

3 | METHODOLOGY & DESIGN

3.1 | Research Method and Techniques

This research follows a deductive methodology within a quantitative research paradigm. The target population consists of healthcare employees in Faisalabad, although a specific sample frame is unavailable. As a result, non-probability convenience sampling has been employed for this study. Primary data was gathered through an online questionnaire survey, with responses collected via Google Forms. This tool was selected due to several practical and methodological advantages that align with the study's requirements and context. Firstly, Google Forms is a cost-effective and time-efficient platform for distributing surveys to a broad audience, especially when targeting geographically dispersed respondents. Secondly, the online nature of the tool ensures convenience and flexibility for respondents, allowing them to complete the questionnaire at their own pace and preferred time, which can improve response rates and data quality. It also facilitates anonymity and confidentiality, which are critical for encouraging honest and unbiased responses. Moreover, google forms offers real-time data collection and automatic compilation, which reduces manual entry errors and accelerates the data analysis process. It also allows the researcher to monitor progress instantly.

3.2 | Scale and Measures

All constructs in this study were measured using a 5-point Likert Scale, adapted from previous research. The dependent variable, "Supply Chain Processes," was assessed using a 5-item scale ranging from 1 (Always) to 5 (Never). The remaining constructs were measured on a scale from 1 (Strongly Agree) to 5 (Strongly Disagree). The constructs used in this study, along with their sources and the number of items used to measure each, are as follows:

Supply Chain Processes (SCP): Measured using 3 items adopted from Chan-Hoong and Soon (2011).

Artificial Intelligence (AI): Measured using 3 items based on Chan-Hoong and Soon (2011).

Supplier Collaboration and Relationships (SCR): Assessed through 3 items taken from Chan-Hoong and Soon (2011).

Digital and Intelligent Environment (DIE): Evaluated using 3 items sourced from Chan-Hoong and Soon (2011).

Production Management (PM): Measured with 3 items drawn from Chan-Hoong and Soon (2011).

4 | RESULTS AND DISCUSSION

4.1 | Demographics of the Respondents

The findings of this study begin with an examination of the respondents' demographics. The questionnaire survey yielded 121 replies. During the first analysis, 13 replies were recognized as outliers and eliminated. This increased the total sample size to 108. Table 2 shows the frequency and percentage distribution of the sample by gender, age, organizational sector, and professional experience level.

Table 1

Table 1: Demographic Characteristics

Demographic Characteristic		Frequency	Percentage
Gender	Male	95	87.9%
	Female	13	12.1%
Age	Below 20	0	0.0%
	21-30	96	88.8%
	31-40	10	9.2%
	Above 40 years	2	1.8%
	50 or Older	0	0.0%
Organization sector	Healthcare	73	67.5%
	Technology /IT	18	16.6%
	Finance	4	3.7%
	Education	1	0.9%
	Others	12	11.1%
Professional experience	0-4 years	27	25.0%
	5-9 years	69	63.8%
	10-14 years	8	7.4%
	15-19 years	3	2.7%
	20 years or above	1	0.9%

The demographic characteristics of the respondents reveal that 87.9% are male and 12.1% are female. Additionally, 88.8% of the respondents fall within the 21-30 age group, 9.2% within the 31-40 and 1.8% in age group above 40 with 67.5% working in the healthcare sector, 16.6% in technology/IT, 3.7% in finance and 0.9% in education in Pakistan. Furthermore, 63.8% of the respondents have between 5 to 9 years of relevant professional experience.

4.2 | Descriptive Statistics

Table 3 shows the descriptive data for each concept in the research. Skewness and Kurtosis are used to determine the normalcy of data. Hair et al. (2012) define normally distributed data as having Skewness values of ±1 and Kurtosis values of ±3 for each construct.

Table 2 Descriptive Analysis

Construct	Mean	Std. Deviation	Skewness	Kurtosis
Supply Chain Processes(SCP)	1.873	0.470	-0.238	-0.285
Artificial Intelligence (AI)	1.324	0.601	0.170	2.496
Supplier Collaboration and Relationships (SCR)	2.942	0.762	-0.764	2.597
Digital and Intelligent Environment(DIE)	2.859	0.651	0.280	0.085
Production Management (PM)	2.842	0.807	-0.823	0.899

The skewness values for all constructs fall within the acceptable range, with the highest being Digital and Intelligent Environment (DIE) at SK=0.280, followed by Artificial Intelligence (AI) at SK=0.170. Additionally, the Kurtosis values for all constructs are within the standard reference range. Therefore, the data for this study exhibits a normal distribution, which supports the use of regression analysis.

4.3 | Reliability analysis

The reliability of a construct is determined by the Cronbach's Alpha and CR. Hair et al (2012) states that values above 0.7 are considered acceptable, with 0.6 being the minimum threshold; Table 3 presents the Cronbach's Alpha and Composite Reliability scores for each construct. All the constructs have exceeded the minimum threshold except for Supplier Collaboration and Relationships (SCR), which is slightly lower at 0.784. These results indicate a strong internal consistency as all constructs are above the minimum level i.e. 0.7.

How well one instrument's scores match those of other instruments measuring the same construct is known as convergent validity. Average Variance Extracted (AVE) is used to evaluate this; convergent validity is considered satisfactory if the value is more than 0.50 (Hair et al., 2012). Convergent validity of the concept is improved by a greater AVE. All of the constructs in Table 4 have AVE values over 0.50, and the data satisfies convergent validity requirements with reliability above 0.70.

Table 3 Reliability Analysis

Construct	Items	Cronbach's alpha	Composite reliability	AVE
Supply Chain Processes (SCP)	3	0.886	0.889	0.526
Artificial Intelligence (AI)	3	0.860	0.860	0.781
Supplier Collaboration and Relationships (SCR)	3	0.779	0.784	0.695
Digital and Intelligent Environment (DIE)	3	0.805	0.806	0.720
Production Management (PM)	3	0.765	0.768	0.680

4.4 | Discriminant Validity

Discriminant validity assesses how distinct and unique each construct is. Several criteria can be used to evaluate discriminant validity, including the Fornell-Larcker criterion, cross-loadings analysis, and the Heterotrait-Monotrait (HTMT) ratio of correlations. The HTMT ratios have been calculated and shown in Table 5. To meet the discriminant validity requirement, the HTMT value between any two constructs should be below 0.90 (Henseler et al., 2015). Based on the values in Table 4, it is evident that all HTMT values are below 0.90, indicating that the constructs in this study are indeed unique and distinct.

Table 4 HTMT Rations Correlation Analysis

Constructs	AI	DIE	PM	SCP	SCR
Artificial Intelligence					
Digital and Intelligent Environment(DIE)	0.167				
Production Management (PM)	0.132	0.236			
Supply Chain Processes (SCP)	0.705	0.298	0.213		
Supplier Collaboration and Relationships (SCR)	0.409	0.169	0.250	0.498	

The correlation coefficients for every pair of variables are displayed in Table 5. It shows that Supply Chain Processes (SCP) are positively correlated with Production Management, Artificial Intelligence (AI), and the strength of the Digital and Intelligent Environment (DIE). Furthermore, SCP and AI as well as Supplier Collaboration and Relationships are positively correlated.

Multicollinearity among components is also found by correlation analysis. Multicollinearity is demonstrated when the correlation coefficient between two constructs falls between 0.9 and 1 (Bell and Bryman, 2007). Since none of the correlation values in this study fall within this range, each construct is regarded as distinct and unique.

Constructs	AI	DIE	PM	NP	SCP	SCR
Artificial Intelligence	1					
Digital and Intelligent Environment (DIE)	0.759	1				
Production Management (PM)	0.591	0.608	1			
Supply Chain Processes (SCP)	0.719	0.766	0.784	1		
Supplier Collaboration and Relationships (SCR)	0.647	0.705	0.772	0.81	1	

4.5 | Overall Model Regression Test

Multiple regression analysis is used to evaluate the entire model in order to investigate "Generative AI and its impact on Supply Chain Performance." Table 6 displays the condensed results from the whole regression model.

Table 6 Regression Results of Overall model

Construct	Mean	Std. Deviation(Beta)	T	P-value
AI >DIE	0.759	0.023	32.443	0.000
AI >PM	0.592	0.043	13.584	0.000
AI >SCR	0.649	0.044	14.739	0.000
DIE>SCP	0.339	0.030	11.408	0.000
PM>SCP	0.336	0.042	7.873	0.000
SCR>SCP	0.315	0.038	8.202	0.000

Results from table 6 are deemed significant if the p-value is less than 0.05 (Nolan & Heinzen, 2007). All the p-value are less than 0.05, so all results of constructs are significant. Moreover, all the std. deviation are more than zero, it shows the significant results.

Table 7 R-Square Values

Construct	Mean	Std. Deviation(Beta)	T	P-value
AI >DIE	0.759	0.023	32.443	0.000
AI >PM	0.592	0.043	13.584	0.000
AI >SCR	0.649	0.044	14.739	0.000
DIE>SCP	0.339	0.030	11.408	0.000
PM>SCP	0.336	0.042	7.873	0.000
SCR>SCP	0.315	0.038	8.202	0.000

Table 7 illustrates the collective impact of all predictors—Artificial Intelligence, Production Management, Digital and Intelligent Environment, and Supplier Collaboration and Relationships—on Supply Chain Processes (SCP). The total effect is 77.9% ($R^2 = 0.779$, $P < 0.05$, $F(4, 402) = 34.56$, $p < 0.05$), demonstrating a statistically significant influence (Bryman, 2015). As the hypothesized model indicates a good fit, the subsequent sections will analyze the individual effects of each predictor.

5 | CONCLUSION

The findings of this study provide empirical support for all proposed hypotheses and directly address the corresponding research questions. Each relationship explored—between Artificial Intelligence (AI) and constructs such as Supplier Collaboration and Relationships (SCR), Digital and Intelligent Environment (DIE), and Production Management (PM)—demonstrates a statistically significant and positive effect on Supply Chain Processes (SCP) within the healthcare context of Faisalabad. These results align with prior research highlighting AI's role in enhancing supply chain integration and sustainability (Toorajipour et al., 2021; Smail Benzidia & Makaoui, 2021; Collins et al., 2021). Therefore, it is strongly recommended that the authors structure the discussion of results by explicitly linking each research question to the relevant objectives and hypotheses, supported by comparative analysis with earlier studies. For instance, RQ1, focusing on the overall influence and strength of AI on SCP, is addressed through direct effects and mediation pathways (H1, H2, H3, H4–H6), which reflects previous work suggesting AI and big data analytics are transformative tools for supply chain performance (El-Kassar & Singh, 2019; Nasiri & Uta, 2020; Gallo, 2023). RQ2, RQ3, and RQ4 explore the mediating roles of SCR, PM, and DIE respectively (H7–H9), and the results confirm their significant contributions, consistent with literature on dynamic capabilities and hospital-supplier collaboration (Kuo, 2017; Kamble & Centobelli, 2020). Anchoring the discussion within the Resource-Based View (RBV) theoretical framework will further strengthen the interpretation, as it positions AI and its associated constructs as strategic capabilities that enhance supply chain performance (Gottlieb & Iansiti, 2019; Shukla, 2011). By contextualizing these findings with prior literature and highlighting both theoretical and practical implications, the authors can offer a coherent, insightful, and impactful narrative (Ebinger & Omondi, 2020; Gülçin Büyüközkan & Göçer, 2018; Liu & Fang, 2018).

5.1 | Managerial and theoretical Implications

The application of AI in healthcare supply chain operations has several managerial implications. First, AI can assist in demand forecasting and inventory management, helping managers optimize stock levels and reduce waste, leading to enhanced efficiency and cost savings. Second, AI can improve procurement processes by evaluating supplier performance and identifying areas for cost reductions, enabling better supplier selection and negotiation. Third, AI can enhance tracking and tracing of medical supplies, offering greater visibility into the supply chain and allowing managers to identify and address bottlenecks or inefficiencies. Finally, AI's integration into healthcare supply chain operations may require managers to invest in training programs to ensure staff can effectively collaborate with AI systems and leverage the technology to its full potential. Overall, AI in supply chain operations can lead to improved decision-making, cost reductions, increased efficiency, and a need for ongoing skill development. Key contributions of this study include:

- The identification of Digital and Intelligent Environment as a mediator between Artificial Intelligence and supply chain performance (SCP).
- Highlighting the mediating role of Supplier Collaboration and Relationship in linking AI to supply chain performance, emphasizing the importance of technology integration in improving processes.
- Suggesting that future supply chain theories should focus on the critical role of technology in enhancing production management efficiency, ultimately improving supply chain processes.
- Recommending that organizations invest in advanced technologies such as Chatbots, ChatGPT, and other AI tools to streamline routine processes like emails, calls, and chats.
- Encouraging the integration of automation and real-time tracking in the healthcare sector to align with sustainability goals by optimizing storage and reducing excess inventory.

Grounded in the Resource-Based View (RBV), this study offers several theoretical implications by conceptualizing Artificial Intelligence (AI) and its associated constructs as strategic organizational resources that enhance healthcare supply chain performance. AI, when applied to core functions such as demand forecasting, inventory management, supplier evaluation, and real-time tracking, fulfills the criteria of being valuable, rare, inimitable, and non-substitutable (VRIN), making it a key enabler of sustained competitive advantage (Toorajipour et al., 2021; Smail Benzidia & Makaoui, 2021). The study identifies the Digital and Intelligent Environment (DIE) as a dynamic capability that enhances the operational impact of AI by enabling real-time data processing and agile decision-making, supporting the RBV's extension into dynamic capability theory (Nasiri & Uta, 2020; Gülçin Büyüközkan & Göçer, 2018). Additionally, the mediating role of Supplier Collaboration and Relationships (SCR) reflects the importance of relational capital as a resource that is socially complex and difficult to replicate, further reinforcing AI's value through strengthened inter-organizational coordination (Kuo, 2017; Kamble & Centobelli, 2020). AI's contribution to enhanced production management capabilities demonstrates the formation of embedded core competencies that drive operational excellence—competencies that are path-dependent and unique to organizations that integrate such technologies effectively (Gallo, 2023; Collins et al., 2021). Lastly, the study suggests that future supply chain theories should incorporate technology-oriented resources, such as Chatbots, ChatGPT, and automation systems, as essential components of the resource portfolio, thus expanding RBV to accommodate the strategic importance of digital technologies in modern healthcare supply chains (Shokrollahi & Yazdani, 2022; Al Zarooni & Matar, 2023). Collectively, these findings reinforce RBV's relevance in the digital age and highlight AI as a transformative force in reshaping supply chain theory and practice.

5.2 | Limitations and Future Research

This study focused on healthcare employees in Faisalabad, specifically within the healthcare sector. Future research could explore different sectors across Pakistan. The study utilized five variables, with four being independent and one dependent. The study explored how healthcare organizations can successfully adopt Generative AI solutions to enhance supply chain performance, considering aspects like organizational preparedness, managing change, and involving stakeholders. It also assessed the overall effect of Generative AI on key roles and perspectives related to the implementation of AI in optimizing lean supply chain processes. Future studies could not only examine attitudes toward AI but also focus on the attitudes toward individual roles, helping to identify effective practices across different fields. Some limitations of this study include:

- A small sample size relative to the large population
- Limited available time for data collection
- Change management issues
- The focus on the overall impact of Generative AI on key roles and attitudes could be expanded in future studies to specifically explore attitudes toward individual roles and how they contribute to implementing effective practices in various sectors.

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