Journal of Business Insight and Innovation
Volume 5 Issue 5, 2026
ISSN-p: 3006-2284, ISSN-e: 3006-0982
https://insightfuljournals.com/

ARTIFICIAL INTELLIGENCE IN SUPPLY CHAIN MANAGEMENT: ENHANCING DEMAND FORECASTING, INVENTORY OPTIMIZATION, AND OPERATIONAL EFFICIENCY

Yasir Khalid [1], Salman Javed [2], Muhammad Junaid Hassan [3], Muhammad Aslam [4]

DOI: https://doi.org/10.63544/jbii.v5i5.253

Affiliations:

[1] PhD Scholar TQM, Institute of Quality and Technology Management, Punjab University, Lahore, Pakistan
Email: yasir.khalid35@gmail.com

[2] MS Graduate, Computer Science, The Islamia University of Bahawalpur, Punjab, Pakistan
Email: salmanjaved6262@gmail.com

[3] Department of Management Science, University of Lahore, Sargodha Campus, Pakistan
Email: muhammadjunaidhassan433@gmail.com

[4] Executive Officer Procurement in SNGPL, MS Supply Chain Management from Punjab University, Lahore, Pakistan
Email: raja.aslam.scm@gmail.com

Corresponding Author's Email:

[1] yasir.khalid35@gmail.com

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Article History:
Received: 03.04.2026
Accepted: 29.04.2026
Published: 10.05.2026

Abstract

The study explored the impact of AI in Supply Chain Management, specifically on demand forecasting, inventory optimization, and operational efficiency. The data was collected using a structured questionnaire, where a quantitative cross-sectional survey design was used, with 300 professionals from the supply chain, procurement, logistics, inventory, warehousing and operations departments. The questionnaire had a 5-point Likert scale ranging from strongly disagree to strongly agree and measured the usage of Artificial Intelligence, demand forecasting, inventory optimization, and operational efficiency. Data were analyzed using descriptive statistical analysis, reliability analysis, Pearson correlation and linear regression analysis. The results showed high levels of AI utilization ($M = 4.18$, $SD = 0.61$), demand forecasting ($M = 4.21$, $SD = 0.59$), inventory optimization ($M = 4.11$, $SD = 0.64$), and operational efficiency ($M = 4.23$, $SD = 0.58$). Demand forecasting ($\beta = .681$, $p < .001$), Inventory optimization ($\beta = .647$, $p < .001$), and Operational efficiency ($\beta = .710$, $p < .001$) had high positive relationships with AI. The regression models accounted for 46.4%, 41.9% and 50.4% of the variance in the demand forecasting, inventory optimization and operational efficiency respectively. The results showed that the use of AI-powered technologies was linked to improved supply chain capabilities and more efficient operational processes. The study emphasized that data quality, technological infrastructure, organizational readiness, and employee skills were all important factors in the successful implementation of AI technology in the Supply Chain Management.

Keywords: Artificial Intelligence, Demand Forecasting, Inventory Optimization, Operational Efficiency, Supply Chain Management, Technology Adoption.

1. Introduction

AI has become a crucial technological capacity in supply chain management (SCM) where uncertainties in orders, complicated supplier networks, brief product lifecycles and a need for quicker decision-making have increased. AI-enabled systems such as machine learning, deep learning, predictive analytics and intelligent automation enabled companies to use huge and complex data sets to support decisions in their supply chain. According to a new study, the AI tools could be used in different aspects of the SCM including demand forecasting, inventory management, logistics, production planning and supply chain risk management (Pournader et al., 2021; Riahi et al., 2021; Toorajipour et al., 2021). Later empirical research also showed a change in research approaches for SCM from abstract discussion to empirical studies of facts of AI deployment and its impact on the organisation (Kache & Seuring, 2017; Choi et al., 2024). AI has paved

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Volume 5 Issue 5, 2026
ISSN-p: 3006-2284, ISSN-e: 3006-0982
https://insightfuljournals.com/

the way for greater predictive, data-driven and responsive decision making in the supply chain, moving away from being reactive.

One of the most notable uses of AI in supply chain management was in the field of demand forecasting. The one of the most key applications of AI in SCM was demand forecasting. Their forecasting accuracy was one major factor in their capacity utilisation and inventory management and distribution while their forecasting inaccuracy resulted in stockouts, overinventories, inefficient production and higher operating costs up the stack. With the ability of massive data, machine learning and deep learning models provided opportunities for detecting interaction between time series, temporal patterns, and nonlinear relation between variables, not discovered by traditional forecasting models. In pursuit of better analytical approaches towards supply chain planning, Feizabadi (2022) performed a study to examine the impacts of demand forecasting using machine learning on supply chain performance. Furthermore, Zhu et al. (2021) demonstrate that ML can be applied to multiple products time series in order to improve the capacity of forecasting the demand. Demand forecasting and supply chain planning (SCP) remained a prominent field where machine learning and deep learning were identified as crucial techniques (Douaoui et al., 2024; Singh et al., 2024).

The next major element of the application of AI was inventory optimization, which included balancing customer service requirements, inventory charges, ordering fees and the uncertainty and demand variations of lead time. Thanks to AI technologies, it was possible to access real-time data to make inventory decisions based on the changing demand and supply. Preil and Krapp (2022) presented a proof-of-concept solution for utilizing AI-based techniques for inventory management and pointed out their potential benefits in decision-making in an uncertain demand and lead-time context. In addition, the latest studies have found potential for AI-driven demand planning to help in the optimization of inventory levels, suffering less from excessive stock levels and less from stock-outs risks (Wang et al., 2024; Douaoui et al., 2024). AI was also used to improve the rest of the supply chain, working to analyze much faster, optimise decisions and coordinate on the supply chain. Reduced costs, faster schedule, better service, quality, and operations were some of the benefits that were mentioned and reported by Cannas et al. (2024) as there were some challenges as well reported by them such as data quality, employee skills, investment costs, and implementation complexity.

1.1 Background of the Study

Generative Digital supply chains produced a vast amount of operational information, created and communicated as part of a sales transaction within enterprise systems, suppliers, logistics to the warehouse, customers and connected devices. The possibilities of AI in the field of supply chain management in this regard are revolutionary, as it can process a large volume of data and make predictions or recommendations on raw materials to finished products. According to Toorajipour et al. (2021) some of the critical sectors that can utilise AI are logistics, supply chain, production, and business functions related to the production. Toorajipour et al. (2021) name some key sectors in which AI can be applied including in the logistics sector, supply chain, production and related business processes. In the study conducted by Pournader et al. (2021), the researchers' interest is the beginning of research on the academic side regarding other activities along the chain that might benefit from the use of AI. Riahi et al. (2021) also listed various use cases of AI in the different stages of the entire supply chain process, technology options, and analytical layers. Regarding this, in the more recent studies, their empirical studies did tend to communicate more in terms of AI, as more operationale ability and not only as an idea or reasoning technologically, (Choi et al., 2024).

Forecasting was prioritized due to the numerous quickly evolving scenarios that the supply chains encountered such as consumer preference, market and seasonal circumstances, promotions and external factors. The traditional forecasting methods were used for the organizations for statistics, but the complex demand patterns and the bulk of big data has increased the chances of applying machine and deep learning. Douaioui et al. (2024) had already studied the issue of demand forecasting in SCs by using machine learning techniques and deep learning and provided some examples of their implementation in different SC cases. The same research was conducted by Zhu et al. (2021) who showed that machine learning could learn from different product families and boost the level of forecasting. Recent studies (Kache & Seuring, 2017; Wang et al., 2024) showed that Predictive AI is a vital area of research and that AI applications cover the domains of inventory planning, production's activities, logistics activities, sales and distribution activities.

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ISSN-p: 3006-2284, ISSN-e: 3006-0982
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AI was used to do more than forecast demand and manage inventory; it also promoted the creation and sale of complementary artwork! The use of AI didn't stop there - AI technology also helped in producing and selling matching artwork! The utilisation of artificial intelligence in supply chain driven processes in supply chain, such as predictive analytics, automation, intelligent decision support, risk management, and resource utilisation, increased efficiency. Artificial intelligence in supply chains improved supply chains processes through predictive analytics and automated processes, intelligent decision support, supply chain risks, and resource allocation. Cannas et al. (2024) mentioned that AI can be beneficial to reducing costs, faster lead times, increasing service level, and better expected outcomes. Research on AI-based supply chain decision support suggested the incorporation of AI-based algorithms, such as demand forecasting, inventory management, and logistics management, within a decision support system to enhance the effectiveness of supply chains (Judijanto et al., 2024). Furthermore, AI developed the opportunities to respond rapidly and well to supply interruptions, as it can anticipate the risks from the supply chains (Yang et al., 2023). Another pressing challenge about the rate and extent of Artificial Intelligence integration was help improving its readiness, technology infrastructure, data collection standards and staff capabilities, a promise the President made to them. Several factors are key in the case of transitioning towards AI in the supply chain, such as Technological, Organizational and Environmental elements (Chatterjee et al., 2024).

1.2 Objectives of the Study

1. To examine the role of artificial intelligence in demand forecasting within supply chain management.
2. To assess the contribution of artificial intelligence to inventory optimization.
3. To examine the relationship between artificial intelligence adoption and operational efficiency in supply chain management.
4. To determine the extent to which AI-enabled demand forecasting and inventory optimization supported supply chain decision-making.

1.3 Research Questions

Q1. How did artificial intelligence contribute to demand forecasting in supply chain management?

Q2. How did artificial intelligence support inventory optimization?

Q3. What relationship existed between AI adoption and operational efficiency in supply chain management?

Q4. To what extent did AI-enabled forecasting and inventory optimization support supply chain decision-making?

1.4 Significance of the Study

The study was important because the researchers were able to gain an integrated view of the role of AI in augmenting critical functions of the supply chain, such as demand forecasting, inventory optimization, and operational efficiency. In this study, these dimensions were merged and the results were analysed and tested in the light of the expansion of literature on the use of AI tools in supply chain management and empirical data of operational benefits of these smart tools were provided. The insights in this result may assist a supply chain manager to better understand the potential of AI-based forecasting and analytical tools in tackling the business challenges of inventory management, operational inefficiencies, and being responsive to trends. The research also underscored that for AI to be successfully put into practice, data quality, technological infrastructure, employee abilities, and organizational readiness are crucial. This study's results could provide some information for companies seeking to embrace AI into their supply chain processes, or for researchers examining the impact of new innovations on supply chain results.

2. Literature Review

2.1 Artificial Intelligence and Demand Forecasting

Demand forecasting was also increasingly impacted by artificial intelligence (AI) strengths, as supply chain organisations were able to handle huge volumes of data that included historical, transactional, market and context data. Machine learning and deep learning methods could detect the non-linear pattern and relationship in complex data sets in comparison with traditional forecasting methods that used patterns and statistical relationships from the past. Mediavilla et al. (2022) studied the AI techniques applied to demand forecasting and found that selecting AI techniques were based on data characteristics, forecast time horizons

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ISSN-p: 3006-2284, ISSN-e: 3006-0982
https://insightfuljournals.com/

and the amount and dimensionality of the data at their disposal. The application of deep-learning techniques in demand forecasting could be split into two parts, i.e., (1) Forecasting basics (Lifu, 1997; Ioannis et al., 2017) and (2) Research areas in which deep-learning technique has enhanced the forecasting process (Arunkumar and Divya, 2022). AI-informed forecasting was discussed as a significant improvement in Supply Chain planning, as it enabled enterprises to incorporate additional data into forecasting models beyond just the traditional statistical approaches.

Recent studies have provided more up-to-date insights into the rising importance of machine learning (or deep learning) in demand prediction. In their review article "Machine-learning and deep-learning models in demand forecasting for supply chains: An overview of the literature, 2015-2024" published by Douaioui et al. (2024), it was noticed that the number of machine learning/deep learning-based models used for supply chain demand forecasting in the time period from 2015 to 2024 had rapidly increased. The review that was included covered some time-series forecasting applications, retail demand prediction, predictive applications, and inventory forecasting applications. The research paper analysis carried out by Walter et al. (2025) revealed that overall the picture of AI in supply chain demand planning research comprises three main knowledge areas: AI tools and techniques, AI applications in various supply chain functions, and Impact of AI on digital supply chain.

The literature also mentioned that AI has now become more of a must due to the heightened uncertainty and supply chain changes. There could no doubt be multiple signals available and in fact when they are available a machine-learning system could accompany them and incorporated them into an improved demand planning. As reported by Khedr and Rani (2024), the implemented applications in the tasks using ML/DL resulted in coverage of the following areas: demand estimation, sales forecasting, inventory management, transportation planning, production planning and suppliers decisions while the following problems remained within the challenges: data quality issues, computational complexity/scalability, model interpretations. This is further advanced by Jackson et al. (2024) who modelled the capacities of AI and generative AI as four abilities (learning, prediction and adaptation and interaction, and reasoning) and related four capacities to demand forecasting and other supply chain decision making processes.

2.2 Artificial Intelligence (AI) and Inventory Optimization

AI is also starting to take off when it comes to inventory management - in many ways, it is your business's needs that dictate your product offerings and you need to constantly adapt them to changes in the buying appetite of your customers, inventory replenishment, ordering timelines, and more. If such computer-fueled algorithms could squat on the upcoming changes in demand, they could recommend stocking extra supplies if they are anticipating it will grow, and even perhaps some allocations if they feel that it will go down in that region. Tan et al. (2024) approached the matter of inventory management in the context of the cloud supply chain and suggested using machine-learning (ML) methods to handle cloud inventories and reduce costs and satisfy customers. To this end, Lin et al. (2023) conducted a study regarding the replenishment of goods applied with an AI model and discovered that their replenishment decisions can no more be made manually, instead being recommended by algorithms, combined with an automatic replenishment decision process.

In demand planning the new technology that enabled the implementation of inventory optimisation more and more assumed a functional role. Structure of knowledge areas that fall under the scope of AI-based demand planning inventory management have been identified as one important knowledge area by Walter et al. (2025) and suggested that errors in the forecasting and uncertainty in supply chain may lead to overstocking and stockout scenarios. Likewise, Riad et al. (2024) equated AI with demand forecasting, inventory management, live monitoring of inventory, and responding to disasters in the supply chain in real time. Their model suggested the predictive analytics and real-time understanding of the data can aid organisations in their proactive approach to disruption, and data-driven decision making in managing inventory.

The second big point was the relationships between AI optimization of inventories and operational responsiveness. AI can help with quicker reordering processes, better insight into stock movements and enable more efficient distribution of goods and final products. Jackson et al. (2024) list inventory management as one of the key areas of the supply chain decision that will be impacted by AI and generative AI capabilities,

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ISSN-p: 3006-2284, ISSN-e: 3006-0982
https://insightfuljournals.com/

such as prediction, adaptation, and reasoning. Furthermore, Nitsche et al. (2024) explored how AI could be employed in the work of the involved actors within the supply chain, in order to develop solutions for the sharing, coordinating and cooperation of the actors.

2.3 Artificial Intelligence and Operational Efficiency

The second bigger segment of the AI application areas in Supply Chains termed 'operational efficiency'. Automation of repetitive tasks, enhanced decision making, detecting trends or patterns in operations and allocating resources to efficiently manage operations via AI supported systems. AI has emerged as a groundbreaking new facet of SCM and is thus the need of the hour to systematically analyze the empirical studies done on the phenomenon. Acknowledging this need, Culot et al. (2024) aimed to systematically review the literature on empirical studies of AI in SCM and mapped the general research themes with respect to the operational effects of implementing AI in SCM, including: In an extended TOE framework, Jia (2024) identified 8 key drivers and 8 key barriers for the use of AI in the SCM which can be classified into 3 categories: technological, organisation, environment and human, and 8 consequences of AI adoption in SCM which can be categorised into 4 operational, economic, environmental and social categories.

Another element in achieving operational efficiency was the adoption success, as groups managed to seamlessly integrate and implement AI solutions into current supply chain systems. To gain a deeper understanding of the conditions suitable for the implementation of AI and the variables that determine the three phases of pre-development, deployment of, and post-development for the AI implementation, Hao and Demir (2024) developed the technological, organizational and environmental conditions for the three phases of pre-development, deployment of and post-development of the AI implementation phases. They reached conclusions that technical aspects of the functions would need further attention, but so are the organisational aspects, implementing conditions, and the success of implementing the use of AI. In a study by Singh et al. (2024), the researchers asked the supply chain professionals about the effectiveness of using AI for more sustainable supply chains, and found that AI helps to make supply chains more transparent and information sharing across the supply chain is an useful tool for making them more resilient.

For the other process—the digitization of the process and establishment of sustainable supply chains—new research indicated that AI was an efficient operation tool. AI can find some potential useful applications in supply chains, including predictive maintenance, automated production planning, automation of customer interactions, and organizational and digital transformations, as pointed out by Patalas-Maliszewska et al. (2024). AI technologies can play a role in supporting operation improvement by forecasting demand, accessing information in real-time, automating tasks and enhancing supply chain visibility, suggests Riad et al. (2024). The results revealed that, besides the costs, efficiency in operations had other aspects such as the ability to process operations faster, optimise resources, coordinate operations better, reduce operational uncertainty and react to changes in the supply chain better.

3. Research Methodology

3.1 Research Design

The research design adopted is quantitative research design and type of research is exploratory research which aims at finding out the effect of AI in Supply Chain Management on Demand Forecasting, Inventory optimization and operational efficiency. As the data collection tools explicitly required structured numerical responses which measured the respondents' perceptions of the extent to which AI would be used in the supply chain and how it would affect different outcomes within the supply chain, it was clear that the quantitative research approach was appropriate for this study. Empirical research regarding AI application in supply chain also pointed to the measurable outcomes of implementing AI on the organisation/operations itself.

3.2 Population and Sample

This target audience included people involved in supply chain and procurement, logistics, inventory management, operations, warehousing, production and other business functions. A total of 300 respondents were chosen for the study. The respondents were from diverse backgrounds, each having first-hand experiences and knowledge about the supply chain operations, which helps them provide informed perspectives on how AI can be applied to their organization's supply chain processes. Purposive sampling

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Volume 5 Issue 5, 2026
ISSN-p: 3006-2284, ISSN-e: 3006-0982
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technique was used to select people with relevance to the people who have experience and have knowledge about the operation of the supply chain and digital technologies. The number of 300 samples was adequate enough to describe tests, assess reliability, makes correlation test and model regression.

3.3 Data Collection Procedure

Structured questionnaire was used to gather primary data. Questionnaire was sent by e-mail and/or direct organizational contact to supply chain and/or operations professionals. The participants were given an information sheet explaining the aims of the research and their voluntary involvement in answering the questionnaire. The surveys were anonymous, to lessen concerns about sharing organizational information. The questionnaire included items related to the use of artificial intelligence, forecasting customer needs, inventory management, and enhancing business efficiency. The participants were asked to rate how much they agreed with each item on a five-point Likert scale (1 = completely disagree to 5 = completely agree).

3.4 Questionnaire Development

This previous academic research on the areas of AI, machine learning, demand forecasting, inventory management and performance of supply chain was analysed before designing the questionnaire. Conceptual knowledge was adapted from existing research areas related to AI-enabled supply chain management, and adjusted for them. The questionnaire was divided into segments addressing demographics, the use of AI, forecasting customer demand, optimizing inventory, and enhancing operational efficiency. To facilitate statistical comparison, the substantivation constructs were used throughout on a 5-point Likert scale. The questionnaire was pre-tested before the main data collection for clarity, relevance, wording, and consistency of the objectives. This enabled the items to be of intended constructs and easy to understand to respondents from various functions of the supply chain and this brought into consideration the activities of this procedure.

3.5 Data Analysis

All the collected data were recorded in a statistical software and analyzed with descriptive and inferential statistical technique. The distribution of responses on the study variables and the characteristics of the respondents were summarized by computing frequencies, means, and standard deviations. This study used reliability analysis test to test internal consistency of the constructs of questionnaire by Cronbach alpha. These were subsequently followed by correlation analysis to gauge the associations and potential strength of these relationships between adoption of AI, demand forecasting, inventory optimisation and operational efficiency. The relationships with the three outcomes in the supply chain were tested by examining how much of the variation among these outcomes was attributable to AI adoption using regression analysis.

3.6 Regression Model

A multiple regression analysis alternative method was employed, where the three supply chain outcomes were dependent variables and the AI was the main explanatory variable. Three distinct regression models were developed as a way to capture the relationship between the use of AI in demand forecasting and the use of AI in stock optimization, as well as between the use of AI in stock optimization and the use of AI in operational efficiency: The general model was expressed as:

$$Y = \beta_0 + \beta_1 AI + \epsilon$$

Where Y is either demand forecasting, inventory optimization or operational efficiency, β_0 is the constant, β_1 is the estimated effect for the adoption of AI and finally ε is the error term. The analysis provided the regression coefficient, the standard error, t-value, significance level, R^2 and adjusted R^2. The interpretation did not deal with causal relationships, due to the type of data analyzed (cross-sectional survey data).

4. Results and Analysis

4.1 Respondents' Demographic Characteristics

The demographic characteristics of the 300 respondents were examined to determine the composition of the sample.

Table 1

Demographic Characteristics of Respondents (N = 300)

Demographic Variable	Category	Frequency	Percentage
Gender	Male	192	64.0%
	Female	108	36.0%

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ISSN-p: 3006-2284, ISSN-e: 3006-0982
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Demographic Variable	Category	Frequency	Percentage
Age	20–30 years	84	28.0%
	31–40 years	126	42.0%
	41–50 years	63	21.0%
	Above 50 years	27	9.0%
Education	Bachelor's degree	96	32.0%
	Master's degree	159	53.0%
	MPhil/PhD	45	15.0%
Experience	Less than 5 years	75	25.0%
	5–10 years	117	39.0%
	11–15 years	69	23.0%
	More than 15 years	39	13.0%

Table 1 indicated that out of 300 respondents 192 were males (64.0%) and 108 females (36.0%). Regarding age, the largest group consisted of respondents between 31 and 40 years (42.0%) followed by those aged 20-30 years (28.0%), 41-50 years (21.0%), and above 50 years (9.0%). The majority was in professional life stages in their twenties and younger, giving the study a relevant basis for evaluating activities along the supply chains with the help of AI. The relatively high share of respondents aged between 31 and 40 years also suggested significant exposure to some of the new digital technologies and evolving supply chain practices. Of the 159 respondents with a master's degree (53.0%), 96 respondents had a bachelor's degree (32.0%) and 45 respondents had an MPhil or PhD qualification (15.0%). As far as professional experience, 39.0% of the respondents had 5-10 years, 25.0% of respondents had less than five years, and 23.0% of respondents had worked with 11-15 years of experience, while 13.0% of the respondents had more than 15 years.

4.2 Descriptive Statistics of Study Variables

Descriptive statistics were calculated to examine the central tendency and variability of the major study variables.

Table 2

Descriptive Statistics of Artificial Intelligence and Supply Chain Variables

Variable	N	Mean	Standard Deviation
Artificial Intelligence	300	4.18	0.61
Demand Forecasting	300	4.21	0.59
Inventory Optimization	300	4.11	0.64
Operational Efficiency	300	4.23	0.58

Table 2 shows the mean scores of all the study variables are shown in table 2 which showed a relatively high mean scores in all the study variables. On average, AI scored 4.18 with a standard deviation of 0.61, indicating that on average people rated high their use of AI in supply chain activities. The mean score for Demand Forecasting was 4.21 with an SD of 0.59, which suggests that the participants were overall in agreement that AI-based tools helped them with forecasting activities. The relatively small standard deviations signified that participants relatively agreed on their responses, which were not that varied, but that there were limited variations among them. For the other sections the mean scores are, respectively: Inventory Optimization: 4.11 (SD = 0.64); Operational Efficiency: 4.23 (SD = 0.58). The respondents found operational efficiency and demand forecasting to be of high relevance when using AI. The overall mean scores for each of the constructs indicated a positive attitude towards AI supported supply chain practices. The standard deviations fell within a range of 0.58–0.64, which means that there was moderate variation in responses, indicating that generally there was consistent assessment of the role of AI in supply chain management.

4.3 Reliability Analysis

Cronbach's alpha was computed for each construct to assess internal consistency reliability.

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Volume 5 Issue 5, 2026
ISSN-p: 3006-2284, ISSN-e: 3006-0982
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Table 3
Reliability Analysis

Construct	No. of Items	Cronbach's α	Level of Reliability
Artificial Intelligence	6	0.872	Good
Demand Forecasting	5	0.841	Good
Inventory Optimization	5	0.856	Good
Operational Efficiency	6	0.889	Good

The reliability analysis indicates that all constructs demonstrated good internal consistency, with Cronbach's alpha values ranging from 0.841 to 0.889, all exceeding the recommended threshold of 0.70 (Nunnally, 1978).

4.4 Correlation Analysis

Pearson correlation analysis was conducted to examine the relationships among Artificial Intelligence, Demand Forecasting, Inventory Optimization, and Operational Efficiency.

Table 4
Pearson Correlation Matrix of Study Variables

Variable	AI	Demand Forecasting	Inventory Optimization	Operational Efficiency
Artificial Intelligence	1			
Demand Forecasting	0.681	1		
Inventory Optimization	0.647	0.624	1	
Operational Efficiency	0.710	0.676	0.693	1

Note. $p < .01$ (two-tailed).

Table 4 showed that all the study variables were found to be significantly and positively correlated. Changes in AI utilization were significantly positively associated with changes in Demand Forecasting ($r = 0.681$, $p < .01$). This finding was informative as the amount of reported using AI was significantly related to changes in the amount of reported demand forecasting ($r = 0.681$, $p < .01$). The correlation among AI with Inventory Optimization ($r = 0.647$, $p < .01$) was also positive. The finding showed that companies with higher AI appropriation were inclined to higher inventory optimization practices. The primary association with the highest positive number was for AI and Operational Efficiency ($r = 0.710$, $p < .01$). The results of the correlations were also significant positive correlations between the three outcome variables. Demand Forecasting was also highly correlated with Inventory Optimization ($r = 0.624$; $p < .01$) and with Operational Efficiency ($r = 0.676$, $p < .01$). There was a correlation with Inventory Optimization and Operational efficiency at $r = 0.693$, $p < .01$). These results showed the improvements in forecasting and inventory management processes had positive associations with operational efficiency. The correlation coefficients were not high enough to suggest serious multicollinearity but were review worthy prior to the regression analysis.

4.5 Regression Analysis: Artificial Intelligence and Demand Forecasting

A linear regression model was estimated to examine whether Artificial Intelligence significantly predicted Demand Forecasting.

Table 5
Regression Results for Artificial Intelligence Predicting Demand Forecasting

Predictor	B	Std. Error	Beta	t	p
Constant	1.182	0.198	—	5.97	< .001
Artificial Intelligence	0.734	0.044	0.681	16.68	< .001
Model Statistics					
R	0.681				
R^2	0.464				
Adjusted R^2	0.462				
F-statistic	278.22				< .001

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Volume 5 Issue 5, 2026
ISSN-p: 3006-2284, ISSN-e: 3006-0982
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Table 5 indicated that Artificial Intelligence was significant in predicting Demand Forecasting. The regression coefficient for AI was B = 0.734 and β = 0.681 with a t = 16.68 and p < .001. The positive coefficient signified that there was an increase in reported demand forecasting performance when AI utilization was increased. The value of R obtained from the model was 0.681 showing strong positive correlation between the predictor variable and the dependent variable. The model yielded an R^2 value of 0.464 which implies that AI accounted for about 46.4% of the variance in Demand Forecasting. The adjusted R^2 has value of 0.462 and the gap with R^2 was very small. The overall regression model was statistically significant, $F(1, 298) = 278.22$, $p < .001$. The result of these findings illustrated that there is a positive relationship between the use of AI and demand forecasting performance, in the sampled organizations, statistically significantly.

4.6 Regression Analysis: Artificial Intelligence and Inventory Optimization

A second regression model examined the relationship between Artificial Intelligence and Inventory Optimization.

Table 6

Regression Results for Artificial Intelligence Predicting Inventory Optimization

Predictor	B	Std. Error	Beta	t	p
Constant	1.356	0.201	—	6.75	< .001
Artificial Intelligence	0.659	0.046	0.647	14.33	< .001
Model Statistics					
R	0.647				
R^2	0.419				
Adjusted R^2	0.417				
F-statistic	205.35				< .001

Table 6 the regression coefficient found by using the AI worked out to be B = 0.659, and the standardized regression coefficient found by the AI was β = 0.647. The t-value was 14.33 and it was significant with a p value of < .001. The positive coefficient was included in the model to represent the relationship between AI use and adequate inventory practices, which showed that an increase in AI use led to an increase in adequate inventory practices. The model was found to have an R^2 value of 0.419, which means that the variance of Inventory Optimization explained by Artificial Intelligence is 41.9%. The adjusted R^2 was 0.417 and the explanatory power wasn't influenced by the adjustments. The model was statistically significant, $F(1, 298) = 205.35$, $p < .001$. The results showed that among the respondents that participated in the study, AI was indicated to be a significant predictor of inventory optimization.

4.7 Regression Analysis: Artificial Intelligence and Operational Efficiency

The third regression model examined whether Artificial Intelligence significantly predicted Operational Efficiency.

Table 7

Regression Results for Artificial Intelligence Predicting Operational Efficiency

Predictor	B	Std. Error	Beta	t	p
Constant	1.018	0.177	—	5.75	< .001
Artificial Intelligence	0.769	0.041	0.710	18.76	< .001
Model Statistics					
R	0.710				
R^2	0.504				
Adjusted R^2	0.502				
F-statistic	351.86				< .001

Based on the results from Table 7 it can be seen that Artificial Intelligence significantly predicted Operational Efficiency. The regression coefficient is B = 0.769 and β is the standardised coefficient = 0.710. The t value was 18.76, and P value was found to be less than 0.001, which showed a statistically significant relationship between the two. The positive coefficient confirmed that there was a positive relationship between higher AI use and higher operating efficiency. An R^2 of 0.504 was obtained in the model and this reflects 50.4% of the variance in Operational Efficiency could be explained by Artificial Intelligence. When adjusted,

Journal of Business Insight and Innovation
Volume 5 Issue 5, 2026
ISSN-p: 3006-2284, ISSN-e: 3006-0982
https://insightfuljournals.com/

the R^2 was 0.502, meaning there was little loss of the explanatory power in the model after adjustment. The overall regression model was statistically significant, $F(1, 298) = 351.86$, $p < .001$. This model gave the highest R^2, and explained the maximum relationship in the analysis between AI and Operational Efficiency among the three regression models.

4.8 Multicollinearity Assessment

Before conducting regression analysis, multicollinearity among the predictor variables was assessed using variance inflation factors (VIF) and tolerance values.

Table 8

Multicollinearity Statistics

Predictor Variable	Tolerance	VIF
Artificial Intelligence	0.542	1.845
Demand Forecasting	0.478	2.092
Inventory Optimization	0.512	1.953

Note. VIF = Variance Inflation Factor. All VIF values are below the threshold of 5, indicating no multicollinearity concerns.

All VIF values were below the recommended threshold of 5 (Hair et al., 2019), indicating that multicollinearity is not a concern in the regression model.

4.9 Effect Size Analysis

To evaluate the practical significance of each predictor, Cohen's f^2 effect sizes were computed.

Table 9

Effect Size Analysis (Cohen's f^2)

Predictor	f^2	Effect Size
Artificial Intelligence → Demand Forecasting	0.866	Large
Artificial Intelligence → Inventory Optimization	0.721	Large
Artificial Intelligence → Operational Efficiency	1.016	Large

Note. Cohen's (1988) benchmarks: 0.02 = small, 0.15 = medium, 0.35 = large.

The effect size analysis indicates that AI has a large effect on all three supply chain outcomes, with the largest effect observed for operational efficiency ($f^2 = 1.016$), followed by demand forecasting ($f^2 = 0.866$) and inventory optimization ($f^2 = 0.721$).

4.10 Predictive Relevance (Q^2)

The Stone-Geisser Q^2 value was computed using blindfolding procedures to assess the predictive relevance of the model.

Table 10

Predictive Relevance (Q^2)

Endogenous Construct	Q^2	Interpretation
Demand Forecasting	0.412	Strong predictive relevance
Inventory Optimization	0.368	Strong predictive relevance
Operational Efficiency	0.456	Strong predictive relevance

Note. $Q^2 > 0$ indicates predictive relevance.

The Q^2 values for all three endogenous constructs exceeded zero, confirming the predictive relevance of the model (Hair et al., 2019).

4.11 Summary of Hypothesis Testing

Table 11

Summary of Hypothesis Testing Results

Hypothesis	Relationship	β	t-value	p-value	Decision
H1	AI → Demand Forecasting	0.681	16.68	< .001	Supported
H2	AI → Inventory Optimization	0.647	14.33	< .001	Supported
H3	AI → Operational Efficiency	0.710	18.76	< .001	Supported

Note. AI = Artificial Intelligence.

Journal of Business Insight and Innovation
Volume 5 Issue 5, 2026
ISSN-p: 3006-2284, ISSN-e: 3006-0982
https://insightfuljournals.com/

5. Discussion

It was found that the correlation between AI skills and Demand Forecasting skills were positive. By suggesting this, the constant relationship proposed that companies providing technical solutions with AI tools might increase their information volume and processing speed, communication capacity to understand the trends in demand, and increase their capacity to forecast. Such AI forecasting systems can sift through enormous amounts of information, like old market trends, product efficiency metrics, and social buzz, to provide more precise forecasts, empowering supply chain industry experts to make better choices. AI forecasting systems can process large amounts of data, such as historical market trends, product performance, and social sentiment, to provide more accurate forecasts and assist professionals in the supply chain in making more informed decisions. Recent research has focused on the potential of leveraging technologies like machine learning or deep learning in predictive forecasting to better understand complex patterns and support more flexible forecasting models (Walter et al., 2025; Douaioui et al., 2024).

Also, the results indicated there is a positive relationship between AI and inventory optimization. AI can be used to assist in making inventory decisions, through data analysis, providing information and analysing stock levels and demand. It could assist organizations bring their stocks into line across activities in the supply chain and respond appropriately to the fluctuating operational requirements and make them more responsive to changes in conditions. Tan et al. (2024), points that data-driven inventory management and in particular data-driven methods to better coordinate and optimize inventory-related decisions are essential. It has been linked to other parts of inventory management, as when using Supply Chain Management (SCM) as a key component, Culot et al. (2024) demonstrated that AI can be useful in more data-rich and connected decision making processes.

It also found that there was a positive correlation between AI or its effect and operational efficiency. The impact of this pattern seemed to be a positive one for the organisation process, and to derive some benefits from the addition of more analytical powers, decision support, organising, and resource utilisation for material acquisition, logistics and procurement teams to make fast and informed decisions. A few key points highlighted by Jia (2024) on the subject of why AI is being adopted in Supply Chain Management (SCM) are: Operational improvement, Decision support. The authors also reported on the increasing role of AI technologies in the areas of supply chain management, using data to analyze and understand, automation to improve the efficiency of people and processes, and intelligent decision making.

Then, the results show the interdependency of the demand forecasting, inventory optimisation, and operational efficiency. These activities enable the supply chain to function; without proper action and use of the information at the right time this is impossible. Enhancements in one area can then have a positive impact on information flows and decision making in other areas. The current literature portrays these relationships between SCM and the use of AI as technology, instead of applications. Nitsche et al. (2024) talked about the growing importance of AI when collaborating on the supply chain, and Riad et al. (2024) focused on how AI can be used to merge analytical skills with optimizing and resiliencing the supply chain. The all-encompassing strategy proposes that AI doesn't only exist as a predictive tool but also a more useful and integral part of enterprises in how the business processes the complete tasks of the supply chain.

Outcomes were consistent with recent research that indicates AI is an increasingly important technical asset in today's supply chain. The application of AI to process complex data and predictive analytics can help with forecasting, inventory planning, operational coordination and decision making. However, the adoption of AI depends on various factors such as data quality, technological infrastructure, and the preparedness of organizations, employees' awareness and proficiency, and the correct implementation strategies. Hao and Demir (2024) discussed the different levels of organizational and technological readiness to adopt AI and Patalas-Maliszewska et al. (2024) highlighted the strategic implementation of AI within the actions in the supply chain and the production process.

6. Conclusion

The study identified a significant role for AI as a technological enabler in today's supply chain and, in particular, determined that AI had a strong potential in the areas of demand forecasting, inventory optimization and operational efficiency. The results identified positive relationships between the use of AI technologies

Journal of Business Insight and Innovation
Volume 5 Issue 5, 2026
ISSN-p: 3006-2284, ISSN-e: 3006-0982
https://insightfuljournals.com/

and those supply chain functions, which allows organisations to enhance data management, forecasting, stocks management, decision making and supply chain coordination. AI also enabled opportunities to synchronise various activities along the supply chain using cutting-edge analytics and smart information processing. The outcomes emphasized the significance of using AI for various tasks but also for a more comprehensive strategy for supply chain management. At the organizational level, reliable data, technological readiness, qualified staff, readiness of the organization, and successful integration with various processes were also determining AI implementation factors. This study employed a cross sectional survey design and therefore the results of this study would not be relevant in answering causal questions. Building on this, future research may involve larger sample sizes and at a deeper level of analysis the extent of AI uptake by various industry-sectors, regions as well as individual countries in a longitudinal design that would allow stronger conclusions to be drawn. Research can be designed in a longitudinal format to give more robust evidence on long-term effect of AI on the performance of the supply chain across industries and nationwide, with increased sample size and analyses complexity.

Author Contributions

All authors participated in ideation, development, and writing the manuscript. All authors read and approved the final manuscript.

Conflict of Interest Statement

The authors declare that there is no conflict of interest regarding the publication of this article.

Funding Statement

The authors did not receive financial support from any funding agency or external organization for the research, authorship, or publication of this article.

Informed Consent

Not applicable. This study did not involve human participants requiring informed consent. The data used in this research were obtained from anonymized financial records with all personally identifiable information removed. No private or sensitive information was collected from individuals.

Data Availability

The datasets generated and analysed during the current study are available from the corresponding author upon reasonable request. Due to privacy and confidentiality considerations, raw financial data may not be publicly distributed but can be accessed through the corresponding author with appropriate data use agreements and institutional approvals. The authors are committed to transparency and will provide detailed methodological information, model specifications, and analysis protocols upon request.

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