# Brains Behind the Chains: Exploring the Drivers of Artificial Intelligence (AI) in Modern Supply Chain Management Success

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## ABSTRACT
Artificial Intelligence (AI) in supply chain management is rapidly transforming how manufacturing companies optimize operations and make strategic decisions. However, manufacturers in low-income countries are fraught with persistent challenges, such as inadequate infrastructure, frequent supply disruptions and lack of technical know-how, that hinder AI supply chain management adoption. This study investigates the impact of internal and external factors on AI-driven supply chain management. Using multiple regression analysis, the results reveal that all five variables significantly and positively affect AI-driven supply chain management. Management support ($\beta = 0.411$, $p < 0.05$) emerged as the strongest predictor, underscoring the pivotal role of executive leadership in digital transformation. Workforce digital skill ($\beta = 0.256$, $p < 0.05$) and technology infrastructure ($\beta = 0.215$, $p < 0.05$) were also found to be critical enablers of effective AI-driven supply chain management. Additionally, market complexity ($\beta = 0.103$, $p < 0.05$) and competitive pressure ($\beta = 0.295$, $p < 0.05$) act as external motivators that push firms toward adopting AI technologies to maintain agility and competitiveness. The study concludes that a successful transition to AI-driven supply chains requires a holistic approach that combines internal readiness with strategic responses to external pressures. Therefore, for AI-driven supply chain management to succeed, manufacturing companies must ensure strong support from senior leadership, invest in workforce digital skills training and upgrade their digital infrastructure to support AI integration.

## Keywords
Artificial Intelligence, Supply Chain Management, internal factors, external factors, multiple regression analysis, Technology-Organization-Environment (TOE) Framework

## 1. INTRODUCTION
The manufacturing sector remains a cornerstone of any country's economic growth and industrial development. It plays a critical role in job creation, value addition, technology transfer, and revenue generation (Dubey et al., 2025). Globally, the adoption of advanced technologies has become a critical strategic imperative for firms seeking to maintain competitiveness and operational efficiency. AI helps factories make customized products faster and with fewer mistakes. It also makes it easier to adjust to changes, like delays from suppliers or sudden increases in demand, by spotting problems early and suggesting solutions (Nyamekeh et al., 2025; Aggarwal & Aggarwal, 2023). Artificial Intelligence (AI) is revolutionizing supply chain management (SCM) by enabling real-time data analysis, predictive modeling, automation, and intelligent decision-making (Ejjami & Boussalham, 2024). AI-driven supply chains utilize machine learning, robotics, predictive analytics, and natural language processing to optimize key functions such as demand forecasting, inventory management, logistics, procurement, and customer service (Mohammad et al., 2025). Large corporations have begun leveraging AI in their supply chains to achieve greater visibility, reduce operational costs, and respond swiftly to market changes (Mohammed et al., 2025; Nyamekeh et al., 2025).

Globally, the emergence of Artificial Intelligence (AI) has revolutionized supply chain management (SCM), offering manufacturing firms advanced tools to enhance decision-making, automate routine processes, and respond swiftly to dynamic market conditions (Chenna, 2024; Nahar et al., 2024). AI-driven supply chains leverage a suite of technologies, including machine learning, robotics, predictive analytics, and natural language processing, to improve forecasting accuracy, optimize inventory levels, automate logistics, and enhance supplier collaboration. The integration of AI into supply chain systems represents a paradigm shift from traditional, reactive models to intelligent, predictive, and adaptive operations (Mahadevan et al., 2024; Onukwulu et al., 2024).

In developed economies, manufacturers are already reaping the benefits of AI adoption. Companies are using AI to reduce operational costs, improve delivery times, and gain real-time insights into supply chain performance (Aich et al., 2025; Mohammed et al., 2025). Nevertheless, in developing countries like those in Africa, the adoption of AI in the manufacturing supply chain remains relatively low. Many firms are either unaware of the benefits or face barriers that prevent successful implementation. This is particularly critical in a post-COVID-19 landscape, where digital resilience and technological adaptation have become crucial for business survival and growth (Odumbo & Nimma, 2025; Raghunath et al., 2020).

Despite the increasing global awareness of the potential of AI to transform supply chain operations, manufacturers in developing countries are yet to fully embrace these technologies. Many firms continue to rely on outdated, manual, or semi-digital systems that are incapable of responding efficiently to the demands of modern supply chains (Onukwulu et al., 2024). As a result, manufacturing firms in developing countries often suffer from inventory excess or stockouts, long lead times, poor supplier relationships, and overall low supply chain visibility.

However, despite its importance, manufacturing industries in low-income countries are fraught with persistent challenges that hinder its global competitiveness. These include inefficient production systems, high operational costs, inadequate infrastructure, frequent supply disruptions, and poor inventory control (Nyamekeh et al., 2025; Mohammed et al., 2025). While these challenges are widely acknowledged anecdotally, empirical evidence on how they influence AI adoption in manufacturing sectors remains limited. Thus, the effective management of supply chains has become a strategic imperative for manufacturing firms seeking to optimize operations, minimize waste, and remain competitive in both domestic and international markets.

The slow adoption of AI-driven SCM in developing countries' manufacturing sectors is influenced by a complex interplay of internal organizational factors and external environmental conditions (Elghomri et al., 2025). The problem is not merely technological; rather, it is rooted in deeper organizational and environmental challenges. Internally, the level of management support, the digital skill level of the workforce, and the state of technology infrastructure within the firm can significantly shape adoption outcomes. Externally, factors such as market complexity, including demand uncertainty, regulatory changes, and supply chain volatility, as well as competitive pressure can drive or hinder the willingness of firms to invest in AI technologies (Onukwulu et al., 2024; Aggarwal & Aggarwal, 2023; Ivanov & Dolgui, 2021). Management hesitation, lack of skilled personnel, weak digital infrastructure, complex and unpredictable markets, and low competitive urgency have all contributed to the sluggish pace of AI adoption in the sector (Mohammad et al., 2025).

Despite the growing body of literature on the adoption of Artificial Intelligence (AI) in supply chain management (SCM), a noticeable gap remains in understanding the organizational and environmental predictors that shape AI adoption, particularly in low-income countries. Existing empirical studies have predominantly focused on technologically advanced or middle-income economies, where digital maturity, infrastructure readiness, and institutional support differ substantially from those in less developed countries. For example, prior studies such as Chenna (2024), Mahadevan et al. (2024), and Nahar et al. (2024) focus on AI adoption in global or industry-specific contexts, yet they often emphasize technical benefits or integration challenges without systematically analyzing the organizational and environmental enablers that affect adoption decisions in resource-constrained environments.

Moreover, existing studies such as Mahabub et al. (2025), Mohammad et al. (2025), and Nahar et al. (2024) focus on technical or process-related variables, such as system compatibility, data analytics capacity, or blockchain integration (Mohammad et al., 2025; Mahadevan et al. 2024), with limited attention to management support, workforce digital skill level, or market complexity, factors that are especially critical in low-income economies where institutional fragility and capacity deficits prevail. Similarly, while competitive pressure is acknowledged in some studies (Aich et al., 2025; Ejjami & Boussalham, 2024), it has rarely been examined in conjunction with internal organizational readiness variables to understand their combined effect on AI adoption in SCM.

To the best of our knowledge, no prior study, particularly in low-income countries, has holistically focused on internal (management support, workforce digital skill level, and technology infrastructure), external (market complexity and competitive pressure) factors affecting AI-driven SCM. This represents a critical oversight, as the dynamics of AI adoption in these settings differ markedly due to infrastructure constraints, skill shortages, and rapidly shifting market environments. Therefore, this study addresses this gap by providing an integrated model that explores how both internal and external organizational factors affect AI adoption in supply chain management, focusing on low-income countries.

This study focuses on manufacturing firms operating in low-income countries, particularly those engaged in supply chain-intensive operations such as consumer goods, and food and beverages.

This research is structured into five sections. Section One introduces the study, including the background, problem statement and significance. SectionTwo presents a review of relevant literature and theoretical frameworks. SectionThree outlines the research methodology, including data collection and analysis techniques. SectionFour presents the results and discussion of findings, while SectionFive offers conclusions, recommendations, and suggestions for further research.

## 2. LITERATURE REVIEW

AI-driven supply chain management adoption refers to the extent to which a manufacturing firm incorporates artificial intelligence technologies, such as machine learning, predictive analytics, robotics, and intelligent automation, into its supply chain operations, including procurement, logistics, inventory management, and supplier coordination. In this study, adoption is conceptualized as the willingness, readiness, and actual implementation of AI-based solutions in the supply chain (Elghomri et al., 2025; Mohammad et al., 2025). Management support refers to the degree of involvement, commitment, and strategic backing provided by senior leadership or top management for the adoption of AI in supply chain management. It includes resource allocation, clear communication of vision, policy development, and decision-making that enables AI implementation (Mahabub et al. 2025; Chenna, 2024; Nahar et al., 2024).

Workforce digital skill level refers to the competency and readiness of employees to work with digital and AI-based technologies in supply chain operations. It encompasses technical know-how, data literacy, problem-solving ability using digital tools, and adaptability to technology-driven changes in workflows (Mohammed et al., 2025; Nyamekeh et al., 2025; Adekola & Dada, 2024). Technology infrastructure describes the foundational digital and technical systems that support AI deployment in a manufacturing firm. This includes computing hardware, software platforms, data management systems, internet connectivity, cloud computing capabilities, and cybersecurity frameworks that facilitate the functioning of AI tools in the supply chain (Iseri et al., 2025; Elghomri et al., 2025; Mahadevan et al., 2024).

Market complexity represents the level of unpredictability, volatility, and diversity in customer demand, regulations, supplier dynamics, and market competition that a firm faces. In this study, it captures external environmental factors that influence how a firm manages its supply chain and whether it sees AI as a necessary strategic response (Aich et al., 2025; Ejjami & Boussalham, 2024). Competitive pressure refers to the intensity of rivalry among firms within the manufacturing sector, and the perceived need to innovate or adopt new technologies like AI to gain or maintain market position. It reflects the influence of peer actions, customer expectations, and industry trends on a firm's decision to embrace AI-driven solutions (Aich et al., 2025; Ejjami & Boussalham, 2024).

## Theoretical Framework

The Technology-Organization-Environment (TOE) Framework, developed by Tornatzky and Fleischer in 1990, is a widely adopted model that explains how firms decide to adopt and implement technological innovations. The framework proposes that technology adoption is influenced by three key contextual domains: the technological context, the organizational context, and the environmental context. These domains interact to shape how organizations perceive, evaluate, and implement new technologies. Thus, the TOE framework provides a robust theoretical foundation for examining the determinants of AI-driven supply chain management in the manufacturing sector.

The technological context refers to the internal and external technologies relevant to the firm and includes characteristics such as the perceived benefits, complexity, and compatibility of the innovation. In this study, the technological context is represented by technology infrastructure, which encompasses the digital systems, IT infrastructure, connectivity, and data capabilities required to implement and support AI technologies. Firms with advanced technological infrastructure are more likely to adopt AI because they already possess the necessary tools and platforms to facilitate integration, reduce system incompatibilities, and lower implementation costs.

The organizational context focuses on the internal attributes of the firm that can support or hinder technology adoption. These include factors such as firm size, financial resources, organizational structure, employee competencies, and most importantly, the level of support from top management. In this study, two critical organizational factors are emphasized: management support and workforce digital skill level. Management support reflects the commitment of leadership to innovation and the extent to which they allocate resources and promote a culture of technology adoption. Similarly, a skilled and digitally literate workforce is crucial for the successful implementation and use of AI technologies in supply chain operations. Without adequate human capacity, even the most advanced systems may remain underutilized.

The environmental context refers to the external environment in which the firm operates, including industry characteristics, regulatory frameworks, market volatility, and competitive dynamics. In this research, the environmental context is captured through market complexity and competitive pressure. Market complexity reflects the uncertainty and dynamism of the business environment, including fluctuating customer demand, regulatory shifts, and supply chain disruptions. This complexity may prompt firms to adopt AI technologies as a means of improving agility and responsiveness. Competitive pressure, on the other hand, refers to the degree of rivalry within the industry and the extent to which firms feel compelled to adopt new technologies to stay competitive. When competitors are embracing AI, other firms may follow suit to avoid falling behind.

The TOE framework is particularly relevant to this study because it offers a comprehensive and systematic lens through which the various drivers and barriers of AI adoption in supply chain management can be analyzed. Rather than focusing on technology in isolation, the TOE model acknowledges that adoption is influenced by a firm's internal readiness and the external pressures it faces. For manufacturing firms in Nigeria, where digital transformation is still developing, understanding these three domains is crucial for crafting effective strategies for AI integration.

## Empirical Review

Chenna (2024) looks at how combining AI with human knowledge improves supply chain systems that use SAP. The study shows that while AI helps with analyzing data, making predictions, and automating decisions, human managers add important insight and strategy. Together, they make supply chains stronger and more flexible. The study recommends a teamwork approach where both AI tools and human skills are used to get the best results.

Ejjami and Boussalham (2024) look at how AI can make supply chains faster, more accurate, and better at handling risks. They also point out problems like unfairness, lack of clarity, and data privacy concerns. By reviewing research, they find that AI helps a lot with predicting problems and making better decisions. But to avoid mistakes, they suggest regular checks and creating special roles, like AI quality and monitoring officers, to make sure AI is used safely and properly in supply chain work.

Mahadevan et al. (2024) examine the synergistic application of Blockchain and AI within engineering supply chains, analyzing their combined impact on improving efficiency, reducing costs, and ensuring data integrity. The study reviews existing literature on the integration of blockchain technology and artificial intelligence (AI) for optimizing engineering supply chains and enhancing transparency. Findings show that integrating blockchain technology and artificial intelligence in engineering supply chains have the ability to create immutable, transparent, and decentralized ledgers that streamline transactions, track goods, and authenticate product provenance. The utilization of smart contracts further automates processes, minimizes disputes, and facilitates trust among stakeholders.

Adekola and Dada (2024) explain how AI-based predictive tools can help improve the pharmaceutical supply chain. They present a plan that shows how companies can use advanced data analysis to work more efficiently, manage risks, and make smarter decisions. The study focuses on solving major issues like managing inventory, changing demand, and following regulations, using AI methods like machine learning and forecasting. The plan also highlights what's needed for success, including how to gather and use data, connect AI with existing systems, and make decisions in real time.

Nahar et al. (2024) investigates the integration of AI-driven automation within cloud-based supply chain architectures and examines its impact on operational performance, decision-making accuracy, and resilience. Drawing upon recent data from industry reports, surveys, and global logistics firms, we present a comprehensive analysis of current trends, frameworks, and best practices. Our findings suggest that AI-empowered, cloud-integrated supply chains can reduce lead times, optimize inventory management, improve forecasting accuracy, and ensure greater supply chain resilience against disruptions. Additionally, we demonstrate how real-time analytics and collaborative platforms drive strategic decision-making and stakeholder engagement.

Aich et al. (2025) study how using AI together with cloud systems helps improve supply chain automation, especially for companies dealing with changing logistics needs. They found that global logistics companies using both AI and cloud technology saw big benefits—like cutting transport costs by 20% and improving demand forecasts by 50%. Real-time tracking also boosted customer satisfaction. By linking their logistics and business systems (OTM-ERP), companies reduced manual data entry and managed inventory more effectively.

Mahabub et al. (2025) explain that to improve business performance, companies need to combine AI tools, data-based decisions, and good leadership. The study shows that strong leaders are needed to guide the use of AI and manage digital change. It finds that AI helps businesses work more efficiently, become more innovative, and react quickly to market changes, giving them an edge over competitors. AI also supports long-term growth by helping companies use resources wisely and act in ways that are good for society and the environment.

Mohammed et al. (2025) look at how AI can help businesses better predict customer demand, manage inventory, and make supply chains run more smoothly. By reviewing past studies and real-life examples, they show how AI can make companies more efficient and better prepared for challenges. The study stresses that using AI is important for businesses to stay competitive in today’s fast-changing digital world.

Nyamekeh et al. (2025) explore the benefits and challenges of using AI to make supply chains more visible and sustainable in real time. The study looks at how AI helps with things like predicting demand, improving logistics, cutting waste, and supporting sustainability. It finds that AI can lead to better decisions, more transparency, lower costs, and less harm to the environment. However, it also points out challenges such as limited budgets, poor data quality, the need to train workers, and cybersecurity risks. The study concludes that while AI can greatly improve supply chains, success depends on teamwork, good planning, and investment in technology.

Elghomri et al. (2025) examine the evolving role of AI in driving accountability and transparency within global supply chains, while critically exploring the persistent gap between academic research and practical implementation. Drawing on 421 articles published between 1998 and January 2025, extracted from Scopus and Web of Science, the analysis utilizes VOSviewer for network visualization and clustering. The findings reveal an exponential growth of research in this domain, particularly after 2020, driven by technological advancements and increasing regulatory pressures for transparency and ethical governance. The geographical distribution of contributions highlights India, China, and the United States as dominant knowledge producers, alongside growing engagement from emerging economies such as Malaysia and Morocco.

Iseri et al. (2025) explore how using reverse logistics can help solar panel supply chains by supporting recycling and reuse. They use analysis of variance (ANOVA) and a post-hoc HSD test to predict changes in prices and demand, and include these predictions in a supply chain model to see how well it works. Their method helps lower costs, improve efficiency, and respond quickly to market changes. The study found that using accurate forecasts works just as well, or even better, than using real data. In contrast, using simple averages led to much worse results, showing that advanced forecasting is important for smart and effective supply chain management.

Mohammad et al. (2025) explore how using blockchain and AI can make Jordan's food supply chains better. They combined AI predictions, live blockchain data, and feedback from stakeholders to improve how information is handled and to support smart decisions about sustainability. The AI predicted drops in food waste, carbon emissions, and energy use. They also used decision-making tools (AHP and TOPSIS) to compare different sustainability goals. The results showed that blockchain made tracking much faster and data more accurate, while the AI gave very reliable predictions about sustainability improvements.

## Summary of Empirical Review

**Table 1: Summary of Empirical Review**

| Author(s)/Year | Variables | Method | Findings | Relevance |
|---|---|---|---|---|
| Chenna (2024) | AI, Human expertise, SAP-based SCM | Case study & implementation analysis | AI-human synergy improves SCM performance through predictive modeling and strategic oversight. | Organizational support and human judgment enhance AI adoption and SCM resilience. Relevant to management support. |
| Ejjami & Boussalham (2024) | AI, SCM operations, Risk management, Data privacy | Literature review | AI enhances SCM accuracy and efficiency but requires transparency, audits, and new AI oversight roles. | Highlights need for workforce oversight and transparency; proposes governance roles. Relevant to digital skills, management, and competitive pressure. |
| Mahadevan et al. (2024) | Blockchain, AI, Engineering SCM | Literature review | Combined use of blockchain & AI improves transparency, reduces costs, and automates transactions via smart contracts. | Strong technology infrastructure is key to successful AI-blockchain integration in supply chains. |
| Adekola & Dada (2024) | AI, Predictive analytics, Pharmaceutical SCM | Conceptual framework | AI enables better inventory and risk management; framework outlines success factors for adoption. | AI implementation depends on data systems, integration with existing infrastructure, and trained workforce. Relevant to digital skills and infrastructure. |
| Nahar et al. (2024) | AI, Cloud-based SCM, Decision-making | Review of industry reports & logistics firm data | AI-cloud integration improves forecasting, inventory, and resilience. Promotes real-time analytics and collaboration. | Shows how AI-cloud synergy improves responsiveness; calls for investment in infrastructure and management readiness. |
| Aich, Sengupta | AI, Cloud, | Case study | AI-cloud adoption reduces | Market complexity and |

| | | | | |
|---|---|---|---|---|
| et al. (2025) | Logistics, Automation | | transport costs (by 20%), improves demand prediction (by 50%), and enhances inventory. | technological readiness drive adoption; firms improved cost-efficiency and responsiveness. Relevant to market complexity and competitive pressure. |
| Mahabub et al. (2025) | AI, Strategic leadership, Corporate performance | Theoretical analysis | AI enhances decision-making, innovation, and sustainability when aligned with strategic leadership. | Leaders must champion AI to drive innovation. Strongly relevant to management support and strategic alignment. |
| Mohammed, Sofia et al. (2025) | AI, Demand forecasting, Inventory management | Literature review & case studies | AI improves efficiency and resilience; organizations must address adoption barriers for future gains. | Emphasizes need for skilled workforce and strategic tech investment. Relevant to digital skills and infrastructure. |
| Nyamekeh et al. (2025) | AI, SCM visibility, Sustainability | Literature review | AI aids transparency, cost, and environmental management but needs infrastructure, funding, and stakeholder collaboration. | AI boosts visibility and reduces cost; challenges include upskilling, data integrity, and infrastructure. |
| Elghomri et al. (2025) | AI, Accountability, Transparency in SCM | Bibliometric analysis (VOSviewer) | Rise in AI-SCM research post-2020; dominant contributions from emerging economies; gap between theory and practice. | Significant AI-SCM research growth; developed environments adopt faster due to better infrastructure and market dynamics. Highlights gaps in practical adoption in developing contexts. |
| Iseri et al. (2025) | AI, Reverse logistics, Forecasting, SCM performance | Deep learning, ANOVA, HSD | Advanced forecasting significantly improves SCM performance for PV panels; accurate models outperform simple ones. | Advanced tech tools improve performance, but require technical infrastructure and strategic vision. |
| Mohammad, Al-Ramadan et al. (2025) | AI, Blockchain, Food SCM, Sustainability | Mixed-methods (ML, AHP, TOPSIS) | Integration improves metadata, reduces waste and carbon footprint; AI forecasts explain up to 88% variance in sustainability metrics. | Integration boosted sustainability; findings underscore infrastructure, data management, and leadership buy-in. |

Source: Authors

## 3. METHODOLOGY

The primary instrument for data collection in this study is a structured questionnaire specifically designed to capture relevant data for each of the study variables. The questionnaire comprises closed-ended questions, all measured on a 5-point Likert scale ranging from "Strongly Disagree (1)" to "Strongly Agree (5)", ensuring consistency in responses and facilitating quantitative analysis.

The questionnaire is divided into sections to address different aspects of the research. Section A focuses on demographic and organizational information, providing context for interpreting the data. Section B includes items that measure AI adoption, which serves as the dependent variable in the study. Sections C through G capture data on various independent variables: Section C addresses management support, Section D measures the workforce's digital skill level, Section E focuses on technology infrastructure, Section F covers market complexity, and Section G assesses competitive pressure.

All items in the questionnaire are adapted from previously validated instruments used in related studies on technology adoption. This study adopts a quantitative research design using a cross-sectional survey approach. Participation in the study was voluntary, and respondents were assured of the confidentiality and anonymity of their responses. Informed consent was sought from each participant.

The population comprises supply chain professionals, operations managers, IT personnel, and decision-makers in manufacturing firms operating in low-income countries. These individuals are directly involved in supply chain processes and are considered knowledgeable about their organizations' adoption of technological innovations, including AI. A purposive sampling technique was used to select manufacturing firms that are actively engaged in supply chain activities and have some level of digital infrastructure in Nigeria. Within each selected firm, respondents with relevant roles in technology adoption or supply chain operations were targeted.

## Sample Size Determination

To determine an appropriate sample size for this study, Yamane's (1967) formula for known population sizes was applied. This approach provides a robust statistical guidance for selecting representative sample while accounting for confidence levels and population size. Thus, 500 manufacturing professionals from six (6) manufacturing firms, actively engaged in supply chain-intensive operations such as consumer goods and food and beverages sector formed the population of the study. The sampled manufacturing companies include Nestlé, Unilever, Nigerian Breweries, Guinness, Seven-Up, CHI Limited, Flour Mills, Promasidor and DUFIL Prima Foods Ltd.

These sectors were purposively chosen due to their high dependency on efficient supply chain systems and the increasing relevance of Artificial Intelligence (AI) in optimizing logistics, procurement, demand forecasting, and inventory management. The respondents include mid- to senior-level supply chain managers, IT personnel, operations managers, and executives responsible for technology adoption and strategic planning, as they possess the contextual knowledge required to evaluate organizational readiness and external pressures influencing AI adoption.

Yamane's formula is applied as follows:

$$n = \frac{N}{1 + N(e)^2}$$

Where: n = required sample size, N = population size = 500, e = margin of error = 0.05

$$n = \frac{500}{1 + 500(0.05)^2}$$

$$n = \frac{500}{1 + 500(0.0025)}$$

$$n = \frac{500}{1 + 1.25}$$

$$n = \frac{500}{2.25}$$

$$n = 222.22$$

## Model Specification

The study adopts a multiple regression model to evaluate the influence of internal and external organizational factors on the adoption of AI-driven supply chain management. The functional form of the model is specified as follows:

AI-driven supply chain management = f(Internal Factor, External Factor)

AISCM = f(MGTS, WORK, TECI, MARC, COMP)

$$\text{AISCM} = \beta_0 + \beta_1\text{MGTS} + \beta_2\text{WORK} + \beta_3\text{TECI} + \beta_4\text{MARC} + \beta_5\text{COMP} + \mu$$

Where: AISCM = AI-driven supply chain management, MGTS = Management Support, WORK = Workforce Digital Skill Level, TECI = Technology Infrastructure, MARC = Market Complexity, COMP = Competitive Pressure, $\beta_0$ = Intercept, $\beta_1$–$\beta_5$ = Coefficients of the independent variables, $\mu$ = Error term

## Method of Data Analysis

Descriptive statistics such as mean, standard deviation, and frequency distributions were used to summarize respondents' demographic and organizational characteristics. These statistics provide an overview of responses to the questionnaire items, offering initial insights into the patterns and trends within the data. Following this, correlation analysis was conducted to explore the strength and direction of the relationships between the variables. This helps determine the associations between the independent variables (management support, digital skill level, technology infrastructure, market complexity, and competitive pressure) and the dependent variable (AI-driven supply chain management).

To test the influence of the independent variables on AI-driven supply chain management, multiple linear regression analysis was employed. This technique will enable the study to determine how each internal and external factor contributes to AI technologies in supply chain management. The regression model help identify which variables have the most significant impact and the extent of their influence. Moreover, post-estimation diagnostic tests were conducted to validate the assumptions of the regression model. The Variance Inflation Factor (VIF) was used to detect multicollinearity among the independent variables, ensuring that they are not highly correlated. The Shapiro-Wilk test assessed the normality of the residuals, confirming whether the error terms were normally distributed. The Breusch-Pagan test was used to identify the presence of heteroscedasticity, which would indicate non-constant variance in the error terms. These tests are crucial for ensuring the reliability and validity of the regression results.

# 4. FINDINGS AND DISCUSSION

## 4.1 Descriptive Statistics

Descriptive statistics were used to summarize the demographic characteristics of respondents and the distribution of responses on the key variables. The results were presented using frequency tables, means, and standard deviations.

**Table 2: Demographic Profile of Respondents**

| Variable | Category | Frequency | Percentage (%) |
|---|---|---|---|
| Gender | Male | 130 | 65.0 |
| | Female | 70 | 35.0 |
| Age | 18–30 years | 40 | 20.0 |
| | 31–40 years | 85 | 42.5 |
| | 41–50 years | 55 | 27.5 |
| | Above 50 years | 20 | 10.0 |
| Position in Organization | Supply Chain Manager | 75 | 37.5 |
| | IT Manager | 60 | 30.0 |
| | Operations Manager | 40 | 20.0 |
| | Top Management | 25 | 12.5 |
| Years of Experience | 1–5 years | 60 | 30.0 |
| | 6–10 years | 90 | 45.0 |
| | Above 10 years | 50 | 25.0 |

Source: Authors

The demographic distribution of respondents in this study reflects a diverse and relevant sample of professionals involved in supply chain operations in Nigeria. In terms of gender, 65% of the participants were male, while 35% were female, indicating a moderate level of gender diversity within the respondent pool. The age distribution shows that the majority of respondents (42.5%) were between 31 and 40 years old, followed by 27.5% who were between 41 and 50 years, 20% within the 18–30 years range, and 10% aged above 50. This age structure suggests that most participants were in their prime working years, likely contributing actively to organizational decisions.

Regarding job roles, 37.5% of respondents were Supply Chain Managers, 30% were IT Managers, 20% were Operations Managers, and 12.5% held Top Management positions. This spread indicates a strong representation from key departments responsible for the adoption and implementation of AI-driven supply chain initiatives. In terms of work experience, 45% of the respondents had between 6–10 years of professional experience, 30% had 1–5 years, and 25% had more than 10 years. This indicates that most participants possessed substantial practical experience, which is valuable for providing informed insights into AI adoption within their respective organizations.

**Table 3: Summary Statistics of Variables**

| Variable | Mean | Standard Deviation | Interpretation |
|---|---|---|---|
| AI-driven supply chain management | 3.87 | 0.68 | High Adoption |
| Management Support | 4.01 | 0.71 | Strong Support |
| Workforce Digital Skill | 3.62 | 0.75 | Moderate to High Skill Level |
| Technology Infrastructure | 3.55 | 0.83 | Moderate Infrastructure |
| Market Complexity | 3.26 | 0.79 | Moderate Complexity |
| Competitive Pressure | 3.94 | 0.66 | High Competitive Pressure |

Source: Authors

The results show that the average AI adoption score ($\bar{X}$ = 3.87) is relatively high, indicating that many manufacturing firms have begun implementing AI technologies within their supply chain functions. Management support received the highest mean score ($\bar{X}$ = 4.01), suggesting strong executive-level commitment to digital transformation. The workforce digital skill level ($\bar{X}$ = 3.62) and technology infrastructure ($\bar{X}$ = 3.55) suggest that while firms are moderately equipped and skilled, there is room for improvement in human and digital capacity. Market complexity ($\bar{X}$ = 3.26) reflects moderate uncertainty in the business environment, while competitive pressure ($\bar{X}$ = 3.94) indicates that rivalry and peer innovation are strong motivators for AI adoption.

## 4.2 Correlation Analysis

Pearson correlation analysis was conducted to examine the strength and direction of the linear relationships between the dependent variable (AI Adoption) and the independent variables (Management Support, Workforce Digital Skill Level, Technology Infrastructure, Market Complexity, and Competitive Pressure). The results are presented in the table below.

**Table 4: Correlation Analysis**

| Variables | 1 | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|---|
| AI-driven supply chain management | 1.0000 | | | | | |
| Management Support | 0.6546 | 1.0000 | | | | |
| Workforce Digital Skill | 0.5370 | 0.4811 | 1.0000 | | | |
| Technology Infrastructure | 0.5023 | 0.4692 | 0.4562 | 1.0000 | | |
| Market Complexity | 0.3865 | 0.3314 | 0.3055 | 0.2989 | 1.0000 | |
| Competitive Pressure | 0.6014 | 0.5184 | 0.4128 | 0.3761 | 0.2897 | 1.0000 |

Source: Authors

The correlation matrix shows that all independent variables have positive correlations with AI-driven supply chain management. Management Support (r = 0.654) has the strongest positive correlation with AI-driven supply chain management, indicating that higher managerial commitment is associated with higher adoption levels. Competitive pressure (r = 0.601) also shows a strong positive relationship, suggesting that firms facing higher industry competition are more likely to adopt AI technologies. Workforce digital skill level (r = 0.537) and technology infrastructure (r = 0.502) both demonstrate moderate to strong correlations, implying that internal capabilities are key enablers of AI-driven supply chain management. Market complexity (r = 0.386) has the weakest, though still significant, positive relationship with AI Adoption, suggesting that firms may turn to AI to navigate external uncertainties.

## 4.3 Tests of Hypotheses

Multiple Linear Regression Analysis

A multiple linear regression analysis was conducted to examine the effects of the independent variables on the dependent variable, AI-driven supply chain management.

**Table 5: Multiple Linear Regression**

| Model | R | R Square | Adjusted R Square | Std. Error of the Estimate |
|---|---|---|---|---|
| 1 | 0.752 | 0.566 | 0.553 | 0.456 |

Source: Authors

The model shows a strong positive correlation (R = 0.752) between the observed and predicted values of AI-driven supply chain management. The R-Square value of 0.566 indicates that approximately 56.6% of the variance in AI-driven supply chain management is explained by the independent variables. The Adjusted R-Square (0.553) confirms the model's goodness-of-fit while adjusting for the number of predictors.

ANOVA (F-test)

**Table 6: ANOVA**

| Model | Sum of Squares | df | Mean Square | F | Sig. (p-value) |
|---|---|---|---|---|---|
| Regression | 38.672 | 5 | 7.734 | 37.198 | 0.000 |
| Residual | 29.638 | 194 | 0.153 | | |
| Total | 68.310 | 199 | | | |

Source: Authors

The ANOVA table shows that the model is statistically significant ($F = 37.198$, $p < 0.05$), indicating that the independent variables collectively explain a significant portion of the variance in AI-driven supply chain management.

**Table 7: Coefficients Table**

| Predictor Variable | Unstandardized B | Std. Error | Standardized B | t-value | p-value |
|---|---|---|---|---|---|
| Constant | 0.812 | 0.202 | – | 4.019 | 0.000 |
| Management Support | 0.365 | 0.058 | 0.411 | 6.293 | 0.000 |
| Workforce Digital Skill | 0.231 | 0.066 | 0.256 | 3.500 | 0.001 |
| Technology Infrastructure | 0.198 | 0.062 | 0.215 | 3.194 | 0.002 |
| Market Complexity | 0.105 | 0.051 | 0.103 | 2.059 | 0.041 |
| Competitive Pressure | 0.276 | 0.063 | 0.295 | 4.381 | 0.000 |

Source: Authors

## Interpretation of Results

Management support ($\beta = 0.411$, $p < 0.05$) has the strongest influence on AI-driven supply chain management. This means that a one-unit increase in management support leads to a 0.365-unit increase in AI-driven supply chain adoption, holding all other variables constant. Workforce digital skill ($\beta = 0.256$, $p < 0.05$) is a significant and positive determinant of AI-driven supply chain management. A one-unit improvement in employees' digital competencies corresponds to a 0.231-unit increase in AI adoption. Technology infrastructure ($\beta = 0.215$, $p < 0.05$) also shows a statistically significant and positive effect. For every one-unit increase in infrastructure readiness (e.g., internet connectivity, IT systems, digital platforms), AI adoption improves by 0.198 units. Market complexity ($\beta = 0.103$, $p < 0.05$), while the weakest predictor in the model, still has a statistically significant influence. A one-unit increase in market complexity results in a 0.105-unit increase in AI adoption. Competitive pressure ($\beta = 0.295$, $p < 0.05$) is a moderately strong predictor of AI adoption. A one-unit increase in perceived market pressure from competitors leads to a 0.276-unit rise in the adoption of AI-driven supply chain practices.

## Discussion of Findings

Management support has positive and significant impact on AI-driven supply chain management. This suggests that successful adoption of AI is not merely a technical issue but a strategic one that requires commitment at the executive level. In other words, managerial commitment and strategic backing play a critical role in fostering AI integration. Management support emerged as the most influential predictor of AI-driven supply chain management. This finding aligns with the findings of Mahabub et al. (2025) and Chenna (2024) that underscore the role of leadership in digital transformation initiatives. When top management actively supports AI initiatives, through funding, strategic alignment, and vision, organizations are more likely to overcome resistance to change and effectively integrate AI technologies. This finding reinforces the technology-organization-environment (TOE) framework, particularly the organizational dimension, and reflects the pivotal role that top-level commitment, strategic vision, and resource allocation play in driving innovation. It also highlights that leadership is essential in overcoming resistance and championing AI integration.

Workforce digital skill has positive and significant impact on AI-driven supply chain management. This suggests that manufacturing firms that prioritize talent development are better positioned to leverage the full potential of AI technologies. Human capital plays a central role in AI-driven supply chain management. Firms investing in upskilling and reskilling their workforce are more likely to successfully deploy and use AI tools across their supply chains. As AI technologies become more embedded in supply chain operations, employees need to possess the necessary digital competencies to interact with, manage, and interpret AI systems.

The result reinforces the need for continuous training and development programs that equip workers with digital literacy and data-driven decision-making capabilities. This finding supports the findings of Nyamekeh et al. (2025) and Adekola & Dada (2024) that AI adoption is not only a technological challenge but also a human development issue. Thus, employee competencies and organizational readiness are facilitators of technology uptake. Without a digitally skilled workforce, even well-funded initiatives may fail due to a lack of operational capability. Firms must invest in continuous digital training and upskilling initiatives to ensure that their workforce can adapt to AI-based systems.

Technology infrastructure was also found to significantly influence AI-driven supply chain management. A robust digital infrastructure, comprising reliable internet connectivity, integrated enterprise systems, cloud computing, and IoT devices, forms the backbone of AI deployment. Organizations with solid technological foundation can more easily collect, process, and analyze real-time data, thereby improving operational efficiency. This confirms that digital readiness is a prerequisite for meaningful AI adoption. This finding is consistent with the technological dimension of the TOE framework and the findings of Mahadevan et al. (2024), suggesting that without adequate digital infrastructure, such as data processing capacity, secure cloud access, and software integration, AI adoption may be limited or ineffective. This reinforces the need for firms to prioritize the development of robust IT systems as a prerequisite for digital innovation.

Market complexity has positive and significant impact on AI-driven supply chain management. This suggests that manufacturing firms operating in highly dynamic and unpredictable markets appear more motivated to implement AI as a strategic response to better forecast demand, manage risks, and respond dynamically to market fluctuations. AI tools offer capabilities such as predictive analytics and scenario planning, which enable firms to anticipate changes in demand and adapt their operations accordingly. Although market complexity was the weakest predictor among the variables, it remains a significant factor. This result highlights the reactive nature of AI-driven supply chain management in complex market environments, where adaptability and responsiveness are crucial. This finding aligns with the findings of Aich et al. (2025), Elghomri et al. (2025) and the TOE perspective that uncertain or dynamic external environments can pressure firms to adopt adaptive technologies like AI to enhance agility and responsiveness.

Competitive pressure showed a moderate but statistically significant effect, suggesting that firms are increasingly turning to AI in response to industry competition. In markets where rivals are leveraging advanced technologies, there is a strong incentive for companies to adopt AI-driven solutions to maintain relevance, improve efficiency, and enhance customer responsiveness. In other words, firms facing intense competition are more likely to embrace AI technologies to gain efficiency, differentiation, or strategic advantage. This supports the view that external pressures, particularly competitive dynamics, act as catalysts for technological innovation in the supply chain domain. This finding supports the TOE view that firms are more likely to adopt innovations when competitors do so, in order to maintain or improve their market position.

This result corroborates the findings of Aich et al. (2025) that organizations are more inclined to adopt emerging technologies like AI when they perceive such adoption as critical to maintaining or enhancing market position.

## 4.4 Post-Estimation Diagnostic Tests

To validate the assumptions underlying the multiple regression model, several diagnostic tests were conducted. These include tests for multicollinearity, normality of residuals, and homoscedasticity.

**Table 8: Multicollinearity Test (Variance Inflation Factor - VIF)**

| Predictor Variable | Tolerance | VIF |
|---|---|---|
| Management Support | 0.652 | 1.534 |
| Workforce Digital Skill | 0.698 | 1.433 |
| Technology Infrastructure | 0.681 | 1.468 |
| Market Complexity | 0.745 | 1.342 |
| Competitive Pressure | 0.663 | 1.508 |

Source: Authors

All VIF values are below the commonly accepted threshold of 5, and Tolerance values are above 0.1, indicating no significant multicollinearity among the independent variables. This suggests that the regression coefficients are stable and reliable.

**Table 9: Normality Test (Shapiro-Wilk Test)**

| Test Statistic | Sig. (p-value) |
|---|---|
| Shapiro-Wilk | 0.976 |

Source: Authors

The Shapiro-Wilk test p-value (0.064) is greater than 0.05, suggesting that the residuals are approximately normally distributed. This meets the assumption of normality for regression analysis.

**Table 10: Heteroskedasticity Test (Breusch-Pagan Test)**

| Test Statistic | df | Sig. (p-value) |
|---|---|---|
| Chi-square | 5 | 0.273 |

Source: Authors

The Breusch-Pagan test for heteroskedasticity returned a p-value of 0.273, which is greater than 0.05, indicating no evidence of heteroskedasticity. This confirms that the assumption of homoscedasticity (constant variance of residuals) holds in the model.

In conclusion, the results of the post-estimation diagnostic tests show that the important conditions for using multiple regression have been properly met. First, the Variance Inflation Factor (VIF) values for all independent variables are less than 5, indicating the absence of multicollinearity. This suggests that the explanatory variables are not too closely related to each other. Second, the Shapiro-Wilk test for normality shows a p-value greater than 0.05, implying that the errors (residuals) are normally distributed. Third, the Breusch-Pagan test for heteroscedasticity gives a p-value above the 0.05 threshold, showing that the spread of the errors is constant (homoscedasticity). Taken together, these diagnostic results show that the regression model is statistically reliable, and its findings can be trusted.

# 5. CONCLUSION

This study examined the impact of key internal and external factors on AI-driven supply chain management. Drawing from empirical evidence, the findings reveal that management support, workforce digital skills, technology infrastructure, market complexity, and competitive pressure all have significant impact on the implementation and success of AI in supply chain operations. The study concludes that AI-driven supply chain management in manufacturing sector is not solely driven by technology availability but by a complex interplay of internal capabilities and external pressures. Therefore, a multifaceted approach that combines strategic leadership, human resource development, digital infrastructure readiness, and responsiveness to market dynamics is essential for successful AI integration in the sector.

## 5.1 Recommendations

For AI-driven supply chain management to succeed, manufacturing companies should ensure strong support from senior leadership, including resource allocation and strategic direction. Workforce digital skills should be enhanced through targeted training to enable effective use of AI tools. Companies also need to upgrade their digital infrastructure to support AI integration. In response to market complexity, firms should use AI for forecasting and risk management to stay adaptive. Finally, instead of reacting to competition, businesses should proactively invest in AI to drive efficiency, innovation, and long-term competitive advantage.

## 5.2 Contributions to Knowledge

This study adds to the growing body of literature on digital transformation in emerging economies by providing empirical evidence on the technological, organizational and environmental determinants of AI adoption in supply chains. It validates the relevance of the TOE framework in the manufacturing sector and highlights the relative strength of internal versus external drivers of AI-driven supply chain management.

## 5.3 Limitations and Suggestions

Although the study provided useful insights, it was limited by sample size which was restricted to selected manufacturing firms including consumer goods, and food and beverages, which may limit generalizability across other sectors. Therefore, future studies could conduct comparative analyses between manufacturing and non-manufacturing sectors whether on country-specific basis or across different regions of low-income countries such as Sub-Saharan Africa.

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