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THE EFFECT OF THE INTEGRATION OF ARTIFICIAL INTELLIGENCE ON SUPPLY CHAIN DECISION-MAKING IN THE MANUFACTURING INDUSTRY

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A B S T R A C T :

This paper investigated the effect of incorporating Artificial Intelligence (AI) on supply chain decision making in manufacturing industry, having a focus on demand forecasting with AI, inventory optimization utilizing AI and predictive analytics based on AI. Data were collected from 100 manufacturing firms globally between 2020 and 2025 using a quantitative longitudinal panel study design. Corporate reports and industry databases were used as the secondary data sources. The effect of using AI apps in supply chain decision making was examined through statistical analysis based on Ordinary Least Squares (OLS) regression with the robust standard error pooled. Because the study relies on secondary data and the representative nature of the purposive sample is uncertain, the study is limited. The results show that the use of AI adds 52.4% variance of resolution of decisions of supply chain. It was found that, among all the four factors, predictive analytics showed the strongest positive effect (coefficient = 6.147, $p < 0.01$) followed by demand forecasting (coefficient = 5.712, $p < 0.001$) and inventory optimization (coefficient = 4.983, $p < 0.05$). This value contributes to ongoing debate on AI's effect on supply chain decision making from a variety of manufacturing contexts and barriers to developing regions. Technically, it is an extension of the TOE framework application to AI adoption in supply chains.

Keywords: Artificial Intelligence, Supply Chain Decision-Making, Demand Forecasting, Inventory Optimization, Predictive Analytics, Manufacturing Industry, Technology Adoption.

Introduction

The supply chain manufacturing industry has undergone significant transformation due to technological advancements, beginning with the introduction of computers in the 1950s and 1960s that enabled complex logistics and inventory management (Olorunyomi et al., 2024; Abu et al., 2024). From the 1980s and 1990s, expert systems evolved until the integration of Artificial Intelligence (AI) in the 2000s, which began to revolutionize demand forecasting and inventory optimization with machine learning. Today, the role of technologies such as deep learning, robotics, and the Industrial Internet of Things (IIoT) in Industry 4.0 is to create agile and efficient supply chains (Linda & Chan, 2024). Now, AI is used to make real time decision, predictive analytics and automation in order to improve strategic response and reduce operational costs (Olorunyomi et al., 2024; Linda & Chan, 2024).

In developed nations, AI adoption in manufacturing now exceeds 60%, reflecting a major transition to digital transformation (Zhang, 2025; Singh et al., 2022). Because of the widespread adoption of AI, manufacturers have been able to cut costs, make their operations smoother, and deliver products more quickly. AI has gone beyond operational gains to improve supply chain visibility and reinforce risk management through real-time monitoring and predictive insights (Mohsen, 2023). Such improvements are especially important in today's fast-paced and competitive market, where rapid response and robustness are essential for maintaining a business advantage.

While these advancements have occurred, AI's transformative capacity in manufacturing is still not fully materialized. A large number of businesses are still using AI mainly to analyze data and support decisions, rather than for fully autonomous decision-making, according to Sajja and Meesala (2025). As a consequence, even though AI helps with incremental improvements, it does not achieve the kind of transformational changes expected from full automation. High implementation costs, worries about job loss, a shortage of technical expertise, and organizational reluctance to adopt change have collectively slowed the adoption of more autonomous systems. As a result, the manufacturing industry has not yet reached the point where AI can bring about comprehensive operational transformation.

In East Africa, the manufacturing industry has not progressed much in adopting AI for supply chain management as less than 10 percent of companies have adopted AI based solutions compared to over 60 percent in developed economies (Singh et al., 2022; Olorunyomi et al., 2024). The reason for this gap is largely due to a lack of digital infrastructure, a lack of AI professionals, and the heavy reliance on manual processes (Abu et al., 2024), as 90% of East African manufacturers still use traditional methods. In addition to these barriers, unreliable internet, low technological investment, little government support, high implementation costs, and cybersecurity concerns hinder AI adoption (Mohsen, 2023; Olorunyomi et al., 2024). Internet access has increased significantly, but broadband users rose from 160 million in 2019 to 2022, but most firms have not integrated digital tools in their operations (Linda & Chan, 2024; Olorunyomi et al., 2024). Fragmented supply chains and regulatory challenges make the problem worse, leaving African manufacturers at risk of falling farther behind global competitors (Linda & Chan, 2024).

While the effect of AI driven demand forecasting, inventory optimization and predictive analytics on manufacturing industry supply chain decisions has been researched well, still the findings are inconsistent and mixed. For instance, While the effect of AI-driven demand forecasting on supply chain decision-making in the manufacturing industry has been widely studied, the findings remain inconsistent. Research in countries like China and Sweden indicates that AI can significantly enhance the integration of forecasting with procurement, production, and logistics functions, leading to waste reduction and operational efficiency (Zhang, 2025; Douaioui et al., 2024). In the U.S., studies have shown that AI-based forecasting tools can reduce safety stock levels and help firms better manage demand uncertainty (Mahi, 2024; Rakholia et al., 2024). However, these benefits are highly dependent on the availability of high-quality, integrated datasets, something that remains a major limitation in many developing countries such as India. Additionally, industries with lower digital maturity or resistance to technological change may struggle to fully realize the potential of AI forecasting tools (Saha et al., 2024).

Regarding inventory optimization, AI tools have demonstrated the ability to make supply chains leaner by automating decisions around reorder levels, stock minimization, and inventory turnover. This has been particularly effective in settings where reliable data streams and system integration are already in place. Studies confirm that AI-enabled inventory systems can reduce holding costs and improve service levels through better real-time decision-making (Rakholia et al., 2024). However, challenges persist in environments where data is incomplete or unstructured, and where the cost of implementation outweighs immediate returns. Additionally, some industries, especially those with diverse product lines or unstable demand patterns, find it difficult to standardize AI-driven inventory solutions, limiting the generalizability of positive outcomes (Jones, 2025; Saha et al., 2024).

The application of predictive analytics in supply chain decision-making has also yielded mixed results. In theory, AI-powered predictive models offer the potential to anticipate market shifts, supply chain disruptions, and customer behavior with high accuracy. Empirical evidence from developed markets shows improvements in strategic planning and operational risk management through predictive tools (Nweje & Taiwo, 2025). Yet, in complex and multi-domain environments, particularly in emerging economies, predictive analytics often underperforms due to the inability of AI systems to extrapolate insights beyond narrowly defined datasets. Additionally, the lack of organizational readiness, limited skilled personnel, and fragmented data infrastructure further hinder its effectiveness (Yadav et al., 2024).

Therefore, this literature gap provided a basis for this study to add to the current academic and practical debates by evaluating how the use of AI influences supply chain decision-making in manufacturing. Because earlier research yielded conflicting results and AI has been adopted differently in different regions and industries, the study aimed to supply empirical proof on the effects of AI-driven tools, such as demand forecasting, inventory optimization, and predictive analytics, on supply chain decision quality and effectiveness. To overcome the limitations related to geography, data accessibility, and technology focus in earlier studies, this research analyzed a global set of manufacturing firms over a five-year span. The research aimed to clarify the separate and combined effects of these AI applications on decision-making, as well as to demonstrate how firms at different technological levels could leverage AI to improve both operational performance and strategic agility.

Literature Review

1.1.2 Theoretical Review

1.1.2.1 Technology-Organization-Environment (TOE) Framework

Tornatzky and Fleischer's Technology-Organization-Environment (TOE) Framework, first introduced in 1990, organizes the analysis of how organizations take up new innovations. It analyzes three major factors: These factors are technological readiness, organizational capabilities, and external environmental pressures. The TOE framework, by taking into account these integrated components, clarifies how and why organizations adopt new technologies. Scientists have utilized the TOE framework to analyze how internal and external factors interact to shape innovation results across a range of sectors, and recent studies validate its applicability to the field of emerging digital technologies (Satyro et al., 2024; Nguyen et al., 2022; Prakash, 2024).

The TOE framework is being increasingly used by manufacturing firms to direct their adoption of Artificial Intelligence (AI) technologies. Technologies such as demand forecasting, inventory optimization, and predictive analytics in supply chain operations are now important factors in manufacturing competitiveness. In addition to having the technology, organizations must ensure they are ready with strong leadership, capable workers, and an adaptable organizational design. Moreover, regulatory norms, customer demands, and competitive market pressures are essential environmental drivers for the adoption of AI (Nweje & Taiwo, 2025; Douaioui et al., 2024). As a result, the TOE framework helps firms evaluate and adjust these elements to promote easier adoption of complex technologies.

Evidence from empirical research shows that successful adoption of innovations depends on how well an organization's internal factors and the external setting match, and on the readiness of the technology itself. There is evidence that firms that encourage collaboration, have effective strategic planning, and receive management backing are better able to utilize advanced analytics tools. Achieving this alignment improves operational performance and makes it simpler for organizations to react quickly to market changes, supporting more flexible decision-making (Besiri, 2024). According to Siska et al. (2023) and Nweje and Taiwo (2025). As a result, the TOE framework continues to be important for organizations that want to strategically address the complexities of digital transformation.

1.2.4 Hypotheses Development

Tornatzky and Fleischer's (1990) Technology-Organization-Environment (TOE) framework serves as a structured model for examining the adoption of AI within firms. In supply chain decision-making, the technological dimension refers to AI's ability to handle vast data, reveal patterns, and produce reliable forecasts. The organizational dimension looks at a firm's internal capabilities, including the presence of skilled workers, supportive leaders, and enough finances, to implement AI technologies. Also, the environmental dimension captures external pressures, including shifts in the market, customer demands, and competitor actions, which can motivate firms to adopt AI for better demand forecasting to remain competitive and agile. Consequently, the TOE framework portrays AI-based demand forecasting as a technology that improves decision quality when it is embedded in a favorable organizational and environmental setting.

A strong consensus exists in empirical literature that AI-based demand forecasting enhances the quality of supply chain decisions. Zhang (2025) demonstrated that AI-based forecasting tools strengthen the integration of supply chain activities and support improved performance and decision-making. Jones (2025) demonstrated that AI-based demand forecasting results in more coordinated procurement and logistics activities, yet data quality and high costs act as major barriers, especially for smaller firms. Douaioui et al. (2024) showed that AI models contribute to more accurate demand forecasting, which helps firms minimize waste and enhance product availability. Siska et al. (2023) pointed out that implementing AI-derived recommendations into supply chain strategies is often difficult in complex environments. Although these difficulties exist, the bulk of the evidence indicates that AI-driven demand forecasting enhances decision-making by allowing firms to respond promptly to market developments and changes in demand. Therefore, in this study it was hypothesized that:

H1: The use of AI for demand forecasting has a positive effect on the supply chain decision making in the manufacturing industry

Through the TOE framework, inventory optimization is viewed as a technological advancement that enables firms to plan inventories using data and to replenish stock in real time. This technological capability supports firms in achieving the right stock levels, providing better service, and decreasing inventory-related expenses. The organizational component assesses a firm's readiness to embed these tools into its operational routines, using effective data infrastructure and experienced workers. The environmental context shows how global competition, heightened customer service demands, and supply interruptions make it necessary for firms to manage their inventories more strictly. Consequently, the TOE framework proposes that AI-driven inventory optimization strengthens supply chain decision-making when the technological solutions are embedded in well-prepared organizations that also respond to external pressures.

This theoretical claim is corroborated by empirical studies. Mahi (2024) showed that AI inventory tools can reduce safety stock by 20–30% and improve product availability, thereby strengthening supply chain decision-making. According to Rakholia et al. (2024), the use of AI tools helps organizations control their stock levels by reducing the risk of overstocking or underproduction. Similar to Palanki (2023), it was found that the integration of inventory optimization with demand forecasting contributes to better supply chain performance by lessening risks and increasing efficiency. According to Yadav et al. (2024), inventory optimization tends to face greater difficulties in complex product line and fragmented supply chain environments, where implementation issues remain. In spite of these challenges, the findings together suggest that AI-driven inventory optimization is beneficial for decision-making by improving inventory visibility and responsiveness in manufacturing. Therefore, in this study it was hypothesized that:

H2: Inventory optimization has a positive effect on the supply chain decision making in the manufacturing industry

The TOE framework (Tornatzky & Fleischer, 1990) provides a strong basis for analyzing how and why supply chains adopt and are affected by predictive analytics. With predictive analytics as a technological innovation, firms are able to leverage advanced algorithms and big data to forecast events such as changing demand, possible supplier slowdowns, and future inventory shortages. Within an organization, making good use of predictive analytics depends on employees' data literacy, effective cross-team collaboration, and adequate spending on information technology infrastructure. The presence of unpredictable markets, intense competition, and environmental sustainability pressures motivates firms to adopt tools that improve their ability to make quick decisions. According to the TOE model, predictive analytics becomes a valuable tool for supply chain decision-making when it is supported by both an open organizational context and an adaptive external environment.

This theoretical argument is grounded in several empirical research studies. According to Besiri (2024), predictive analytics greatly enhances decision-making by automatically generating insights and improving resource allocation, but only if data is of high quality and well integrated. According to Nweje and Taiwo (2025), using AI for predictive analytics improves both visibility and the precision of forecasts, thereby helping supply chains stay agile even in complicated settings. According to Siska et al. (2023), predictive analytics improves the precision of forecasts, though the authors recognized the complexity of translating these insights into action in multiple manufacturing contexts. These results together indicate that predictive analytics supports manufacturing firms by enabling them to respond to uncertainty and optimize their supply chain activities. Therefore, in this study it was hypothesized that:

H3: Predictive analytics has a positive effect on supply chain decision making in the manufacturing industry.

1.3 Research Methodology

1.3.1 Research Design

The approach used in this study was quantitative research. Saunders et al. (2019) explain that the main features of quantitative research are the use of numerical data and statistical methods to test and explore variable relationships. A panel study design was employed in this study, together with a longitudinal method, to observe and analyze variations over time. The main purpose for selecting a longitudinal design was to provide a comprehensive analysis of how AI integration has affected supply chain decision-making in the global manufacturing industry from 2020 to 2025.

1.3.2 Study Population and Study Area

A population is defined as the full collection of elements or items that a research study aims to study (Kothari, 2004). The population under study consisted of manufacturing firms from around the world that are either currently using or planning to use AI in supply chain operations. The firms were chosen because their adoption of AI makes them ideally positioned to supply the data required to study the role of AI in supply chain decision-making, including demand forecasting, inventory optimization, and predictive analytics.

1.3.3 Sample Size

A sample represents part of the population from which we can draw conclusions about the entire group (Kothari, 2004). Because of financial, time, and data availability limitations, a purposive sample of 100 manufacturing firms was chosen. Firms were chosen if they currently implement or plan to implement AI in their supply chain management. The analysis of each firm's corporate data spanning 5 years (2020–2025) resulted in 500 firm-year observations. The sampling technique covered a wide range of geographic regions and operational settings, thereby increasing the reliability and applicability of the findings.

1.3.4 Data Collection

The data used in this study were obtained solely from secondary sources, including corporate annual reports, operational records, and global manufacturing industry databases including the FAO and Global Database Manufacturing Industry Database. They were chosen for their ease of access, continual consistency, and dependability. Because the study aimed to evaluate AI's role in supply chain decision-making, secondary data were a sensible and economical way to obtain relevant, extensive, and longitudinal datasets.

1.3.5 Data Analysis

Data analysis involves the process of examining, cleaning, transforming, and modelling data with the objective of uncovering valuable insights, drawing meaningful conclusions, and facilitating informed decision-making. In this study, data analysis was carried out through several stages, including descriptive statistics, correlation analysis, empirical modelling, and hypothesis testing. The collected data was systematically organized and analysed using the Stata software package, which provided clear and comprehensive presentations of the findings. Dynamic panel data regression techniques were applied in the analysis, and following a series of diagnostic tests, pooled Ordinary Least Squares (OLS) regression was selected as the most suitable method to examine the relationships between the dependent and independent variables (Hair et al., 2021; Rasoolimanesh, 2022).

Data Analysis and Results

1.4.1 Sample Characteristics

The study analyzed a balanced panel dataset of 100 manufacturing firms from across all continents, each actively involved in supply chain operations and either using or planning to adopt AI technologies, with data collected over five years (2020–2025) totaling 500 firm-year observations. Firms varied in ownership; private, public, government-owned, and joint ventures, and were selected based on publicly available performance data from sources like the FAO and Global Manufacturing Industry Database. The analysis also accounted for firms' operational experience in supply chain management and AI implementation, categorizing them into four groups by years in operation. Notably, 45% of the firms had over 30 years of experience, indicating a high level of industry expertise, which, consistent with prior research(Ridwan et al., 2023; Harris & Clark, 2024), supports the view that more established firms are more likely to adopt advanced technologies such as AI for enhanced decision-making and performance.

Table 1.2: Years the Company has Operated

Years the Company has Operated	Frequency	Percentage
< 10 yrs	15	15%
10 yrs < but < 20 yrs	25	25%
20 yrs < but < 30 yrs	15	15%
≥ 30 yrs	45	45%
Total	*100*	*100%*

1.5 **Model Analysis and Results**

To further validate the absence of multicollinearity, a Variance Inflation Factor (VIF) test was conducted. As displayed in Table 1.4, all VIF values are below 5 and tolerance values are above 0.2, confirming that multicollinearity is not a significant issue in the model (Rasoolimanesh, 2022).

Table 1.4: Multicollinearity Test Coefficients

Variable	VIF	Tolerance
SCDM	1.181	0.847
IO	1.174	0.852
DF	1.062	0.942
PA	1.021	0.980

1.4.3 Regression Results

The pooled Ordinary Least Squares (OLS) regression analysis examined the impact of AI integration specifically AI-based demand forecasting, inventory optimization, and predictive analytics on supply chain decision-making (SCDM) in the manufacturing industry. The regression model, which accounted for potential heteroskedasticity with robust standard errors, explained 52.4% of the variance in supply chain decision-making (R-squared = 0.524), indicating strong explanatory power. The model's F-statistic of 15.691 and a p-value of 0.000 confirmed statistical significance, demonstrating that AI-driven technologies significantly influence decision-making. AI-based demand forecasting had the largest positive effect, with a coefficient of 5.712 (p-value = 0.000), followed by inventory optimization (coefficient = 4.983, p-value = 0.011) and predictive analytics (coefficient = 6.147, p-value = 0.001).

Based on the regression, AI-based demand forecasting shows the highest and most statistically significant positive effect on supply Therefore, the use of AI in demand forecasting helps firms achieve better and quicker decisions regarding procurement, production planning, and distribution. When firms are able to precisely predict customer needs, they can take steps ahead of time to avoid imbalances in supply and demand, and keep inventory levels down. As a result, supply chain decisions become both more effective and more responsive, which helps manufacturing firms operate more successfully in changing market environments.

The results also demonstrate that inventory optimization is an important driver of better supply chain decision-making, as indicated by a coefficient of 4.983 and a p-value of 0.011. This indicates that AI-based inventory management tools assist in making improved choices about inventory amounts, restocking intervals, and warehouse operations. Applying real-time data and optimization algorithms helps firms manage their inventory so that they do not experience either stockouts or overstocks. As such, supply chain decision-makers can achieve more accurate and affordable decisions, which leads to higher service levels and greater operational efficiency throughout the supply chain.

In addition, predictive analytics was found to be a major driver of supply chain decision-making, as indicated by a coefficient of 6.147 and a p-value of 0.001. This result shows that predictive analytics supports better decision-making by uncovering patterns, trends, and impending disruptions. It empowers companies to decide strategically about supply chain risks, variations in demand, and resource planning. The incorporation of predictive insights into both strategic and operational actions helps firms take proactive measures, rely more on data, and better manage uncertainties, which leads to a supply chain that is more resilient and adaptable.

Table 1.1: OLS Longitudinal Panel Regression of the effect of the Integration of Artificial Intelligence on Supply Chain Decision-Making in the manufacturing industry

score	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
DDM	5.712	1.103	5.18	0.000	3.542	5.712	***
CSM		4.983	1.929	2.58	0.011	8.780	***
IEC	6.147	1.777	3.46	0.001	2.660	6.147	***
Constant	3.264	4.378	0.75	0.453	5.350	3.264	

Mean dependent var	20.194	SD dependent var	9.845
R-squared	0.524	Number of obs	500
F-test	15.691	Prob > F	0.000
Akaike crit. (AIC)	3589.263	Bayesian crit. (BIC)	3620.792

**** p<0.01, ** p<0.05, * p<0.1*

1.5 Discussion

The first hypothesis tested the effect of AI-based demand forecasting on supply chain decision-making. The findings revealed a positive and statistically significant relationship, with a coefficient of 5.712 and a p-value of 0.000, indicating strong support for the hypothesis. These findings support the technological dimension of the TOE framework, as the availability of advanced AI forecasting tools contributes to better-informed and more agile supply chain decisions. This result is consistent with of Douaioui et al. (2024), and Zhang (2025) who demonstrated that AI forecasting enhances accuracy and enables tighter integration across procurement, logistics, and production. These similarities imply that AI tools consistently add value when used to align operations with market trends and customer needs. However, unlike Jones (2025), who noted that data quality and high implementation costs restrict adoption among smaller enterprises, the present study revealed a uniformly positive effect, possibly due to its broader sample of globally dispersed firms. This difference suggests that firm size, digital maturity, and resource availability may influence the extent to which AI forecasting translates into decision-making gains.

The second hypothesis examined the effect of inventory optimization on supply chain decision-making. The results showed a significant and positive relationship, with a coefficient of 4.983 and a p-value of 0.011, supporting the hypothesis. From the organizational dimension of the TOE framework, these findings show how organizational readiness, in terms of data infrastructure, skilled personnel, and system integration. This can enhance the success of AI-enabled inventory optimization tools in improving decision-making processes. The findings are similar to Mahi (2024) and Yadav et al. (2024), who observed that AI applications reduce safety stock, raise service levels, and improve availability. These similarities indicate that AI tools are effective in enabling responsive inventory decisions, particularly where structured data and digital tools are accessible. Yet, while Rakholia et al. (2024) and Palanki (2023) also found that AI prevents overstocking and underproduction, their studies showed the need for continuous model refinement and high-quality data integration. The present study did not identify such constraints, suggesting that in controlled environments or larger firms with adequate infrastructure, AI inventory systems operate more effectively.

The third hypothesis investigated the effect of predictive analytics in supply chain decision-making. The study found a statistically significant positive effect, with a coefficient of 6.147 and a p-value of 0.001. This finding aligns with the results of Besiri (2024) and Palanki (2023), who highlighted its role in boosting proactive decision-making and minimizing operational disruptions. This implies that predictive tools contribute meaningfully to strategic and tactical agility. Still, Siska et al. (2023) and Nweje and Taiwo (2025) identified challenges in applying AI insights within complex supply chains, where fragmented data and implementation hurdles may undermine their impact. In contrast, the current study's strong statistical results suggest that such barriers can be overcome when firms invest in data infrastructure and cross-functional alignment. These differences imply that while predictive analytics holds substantial promise, its effectiveness depends on contextual factors such as data readiness, employee capabilities, and technological integration. From the environmental perspective of the TOE framework, the increasing pressure from competitors and rapidly evolving markets compels firms to adopt predictive analytics to remain agile and competitive in decision-making.

1.6 Managerial implications, conclusions and recommendations

1.6.1 Managerial implications

The results of this research indicate that the use of AI technologies such as demand forecasting, inventory optimization, and predictive analytics makes a strong positive difference in supply chain decision-making for manufacturing companies. Demand forecasting that uses AI improves decision-making by delivering precise and evidence-based predictions about future market requirements. Such insights help managers take prompt and well-informed actions in planning production and procurement. AI systems reduce the element of guesswork, which allows managers to use resources more effectively, keep products available for customers, and manage the risks caused by changing consumer demands.

AI-driven inventory management is vital in helping managers make better decisions about inventory, reordering, and how quickly stock moves. In place of using fixed inventory rules or manual number crunching, AI systems use live data to help managers achieve both cost effectiveness and high service levels. These tools are designed to help decision-makers sidestep typical inventory issues, such as the extra costs from having too much stock or the missed revenue from running out of stock. Because AI automates tasks and continually learns, managers are better positioned to respond to supply chain changes rapidly and confidently.

AI-driven predictive analytics strengthens strategic decision-making by giving managers advance visibility into both emerging risks and opportunities within the supply chain. Predictive analytics enables managers to recognize patterns and trends within complex datasets, which supports their ability to take early action on issues related to suppliers, market movements, and logistics. This proactive insight is necessary for both long-term strategy and crisis response, because it allows businesses to stay resilient and adaptable amid uncertainty. This study's results indicate that AI adoption by manufacturing firms enables more informed and effective decision-making throughout the supply chain, resulting in stronger performance, greater competitiveness, and enhanced resilience.

1.6.2 Conclusions

The study contributes to the ongoing debate on the integration of artificial intelligence in supply chain decision-making within the manufacturing industry, especially in developing regions such as East Africa. It addresses the lack of empirical evidence regarding the effectiveness of AI applications in low-digital environments where adoption remains minimal. The research explores the influence of AI-driven demand forecasting, inventory optimization, and predictive analytics on supply chain decisions, offering insights that contrast with earlier studies focused primarily on developed economies. Through analysis of data from 100 global manufacturing firms over five years, the study reveals that these AI tools have a significant and positive effect on decision quality, filling the gap left by fragmented findings in previous literature and emphasizing the potential for AI impact even in digitally underdeveloped regions.

The research advances the academic conversation through the application of the Technology-Organization-Environment framework, which emphasizes the importance of technological readiness, internal capabilities, and external pressures in AI adoption. Findings demonstrate that firms with varying levels of digital maturity can still improve supply chain decision-making through AI tools when supported with appropriate organizational structures and external enablers. The study reinforces the practical value of AI for operational and strategic decision-making and underscores the urgency for investments in digital infrastructure, skill development, and supportive policies in regions that risk falling behind. These contributions provide a balanced perspective that moves beyond the traditional focus on advanced economies, encouraging inclusive digital transformation in manufacturing.

1.6.3 Recommendations for manufacturing Firms

Given the positive and significant relationship between AI-based demand forecasting and supply chain decision-making, manufacturing firms should integrate AI-based demand forecasting models to align production and procurement with actual market demand, reducing overproduction and stockouts. Continuously evaluating and adjusting AI models based on market changes will enable data-driven decision-making.

Likewise, considering the significant positive influence of AI-based inventory optimization on supply chain decision-making, manufacturing firms should adopt AI-powered inventory optimization systems to manage stock levels, reduce waste, and improve efficiency. Real-time monitoring and adjustments allow for better decision-making on reordering, lead times, and logistics planning, minimizing costs and improving market responsiveness.

Finally, with the positive relationship between AI-based predictive analytics and supply chain decision-making suggests that manufacturing firms should implement AI-based predictive analytics tools to anticipate disruptions, market fluctuations, and demand shifts. Through proactively adjusting production, procurement, and logistics, firms can optimize decision-making, reduce risks, and enhance supply chain efficiency. Regular updates will ensure ongoing accuracy.

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