

Effect of Artificial Intelligence and Supply Chain Technology on Firm Value of Selected Consumer Goods Manufacturing Firms in Nigeria

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ABSTRACT

The rapid diffusion of artificial intelligence (AI), digital analytics, automation and smart supply-chain technologies is transforming the manner in which manufacturing firms forecast demand, manage inventories, coordinate suppliers, optimise production and create shareholder value. Despite the increasing strategic importance of these technologies, empirical evidence on their relationship with firm value in Nigeria remains limited, particularly within the consumer-goods manufacturing sector. This study investigates the effect of artificial intelligence and supply-chain technology on the firm value of selected listed consumer-goods manufacturing firms in Nigeria over the period 2015–2024. The study adopts an ex-post facto research design and uses secondary data extracted from audited annual reports, corporate reports and Nigerian Exchange market information. Top Ten listed consumer-goods manufacturing firms constituted the sample. From correlation and regression analysis, Supply Chain Technology was found to have a negative and statistically significant relationship with Tobin's Q ($\beta = -0.101$, $p = 0.016$), while Artificial Intelligence had a positive but statistically insignificant relationship with Tobin's Q ($\beta = 0.651$, $p = 0.410$). These findings suggest that the relationship between technological adoption and market valuation may be more complex than a simple assumption that greater technology adoption automatically results in higher firm value. It was therefore recommended that Consumer manufacturing firms should not view the acquisition of Supply Chain Technology or Artificial Intelligence as an end in itself. Rather, management should evaluate technology investments based on their expected contribution to operational efficiency, cost reduction, revenue growth, customer responsiveness, and ultimately firm value.

Keywords: Artificial intelligence; supply-chain technology; firm value; Tobin's Q; consumer goods; manufacturing firms; Nigeria; technology adoption; panel data.

INTRODUCTION

Technological transformation has become an important determinant of corporate competitiveness, operational performance, and value creation. Artificial intelligence (AI), machine learning, predictive analytics, cloud computing, the Internet of Things (IoT), enterprise resource planning (ERP), robotics, and other digital technologies are increasingly being integrated into manufacturing activities, including production planning, predictive maintenance, quality control, demand forecasting, inventory management, supply-chain coordination, and logistics. Recent reviews of AI in manufacturing indicate that these technologies are increasingly central to intelligent automation, data-driven decision-making, process optimisation, robotics, supply-chain management, and production planning (Cao et al., 2024; Haq et al., 2024). Empirical evidence further indicates that digital supply-chain transformation and smart technologies can improve operational performance in manufacturing firms (Lee et al., 2024).

Artificial intelligence (AI) has consequently moved beyond an experimental technology to become an increasingly important organisational and strategic capability. AI enables firms to analyse large volumes of data, automate decisions, identify patterns, forecast demand, optimise processes, and support managerial decision-making. Shi et al. (2025) with data from Chinese listed firms, found that AI adoption significantly enhances enterprise value through both direct and indirect channels, with data assets mediating approximately 45% of the total effect. Their findings also indicate that managerial capability strengthens the value generated from AI investment. This suggests that AI creates value not merely through technological adoption itself but through the accumulation and effective utilisation of complementary data and organisational resources

The transformation is particularly important for consumer-goods manufacturers because their operations typically involve complex supply networks, fluctuating consumer demand, inventory requirements, extensive distribution activities, and exposure to supply-chain disruptions. Yu et al (2024) explained that datafication supported by IoT and AI can improve supply-chain performance and innovativeness, with supply-chain resilience acting as an important mediating mechanism. They also found that AI-enabled manufacturing process, automation and cognitive engagement can strengthen manufacturers' resilience and performance.

Meanwhile, Nigerian manufacturing firms operate within an emerging-market context characterised by infrastructure constraints, exchange-rate pressures, inflationary conditions, logistics challenges, energy costs, and supply disruptions. These conditions make technologies capable of improving forecasting, inventory optimisation, production efficiency, logistics coordination, and supply-chain resilience particularly relevant. Oyerogba et al.(2024) found that adoption of modern manufacturing technologies is significantly associated with firm value and also reported that firms in Nigeria adopting newer manufacturing technologies demonstrate better performance. He however noted that, technological failures can equally impose substantial costs on firms. Song et al. (2025) in similar vein explained that AI service failures negatively affect firm value because market can penalise firms when AI-related failures generate concerns regarding accuracy, safety, privacy, or fairness.

Although the technology-performance relationship has received growing attention in Nigeria, relatively limited evidence directly examines the relationship between specific AI and supply-chain technology capabilities and market-based firm value among listed Nigerian consumer-goods manufacturing firms. Existing Nigerian evidence has considered broader modern manufacturing technology adoption, while much of the wider literature has concentrated on operational performance, financial performance, supply-chain resilience, or technology adoption. (Oyerogba et al., 2024).

Against this background, this study investigates the effect of artificial intelligence adoption and supply-chain technology on the firm value of selected listed consumer-goods manufacturing firms in Nigeria over the ten-year period 2015–2024. The study is expected to contribute to the emerging literature by connecting technology adoption with market-based firm valuation within a Nigerian consumer-goods context and by considering AI and supply-chain technology jointly rather than treating technological capabilities as isolated investments.

Artificial Intelligence

Artificial intelligence (AI) refers broadly to computational technologies capable of performing tasks associated with human intelligence, including learning, prediction, classification, pattern recognition, language processing, optimisation, and decision support. In manufacturing, AI applications include predictive maintenance, demand forecasting, quality inspection, production planning, process optimisation, robotics, intelligent automation, and supply-chain management (Cao et al., 2024; Haq et al., 2024)

AI is increasingly regarded as an organisational capability rather than merely a technological asset. Its economic value depends on the firm's ability to combine AI with data, human expertise, managerial capabilities, digital infrastructure, and complementary organisational processes. Shi et al. (2025) showed that managerial capability strengthens the relationship between AI adoption and enterprise value, implying that AI capabilities can become strategically valuable when they are embedded within firm-specific organisational

routines and combined with complementary resources. The acquisition of generic software or technological infrastructure alone may therefore be insufficient to generate sustained competitive advantage. Instead, competitive benefits may arise when firms develop difficult-to-replicate combinations of technology, data, managerial expertise, organisational knowledge, and specialised human capital (Barney, 1991).

Artificial Intelligence and Nigerian Manufacturing Firms

The integration of artificial intelligence into manufacturing have been claimed to influence competitiveness and firm value through improvements in operational efficiency, decision quality, flexibility, and resilience. Haq et al. (2024) identified predictive maintenance, process optimisation, quality control, intelligent automation, robotics, and supply-chain management among the major areas in which AI is being deployed.

Yu et al. (2024) pointed out AI-based demand forecasting can improve inventory planning by identifying patterns in historical and real-time data and generating more accurate estimates of future demand. Improved forecasting can potentially reduce stock outs, excess inventories, and inefficient resource allocation. AI-enabled customer analytics can similarly provide firms with information about consumer preferences and market trends, thereby supporting product planning and marketing decisions. At the production level, AI can support predictive maintenance, process automation, quality control, and real-time operational decision-making. These capabilities can contribute to improved manufacturing resilience and performance

The relevance of these capabilities is particularly strong in emerging-market manufacturing environments because Nigerian firms face significant operating uncertainties associated with inflation, exchange-rate movements, infrastructure limitations, energy costs, logistics constraints, and supply disruptions. Consequently, technologies that improve forecasting, resource allocation, production efficiency, and supply-chain resilience may have important economic implications.

Supply Chain Technology

Supply-chain technology encompasses digital systems and applications used to coordinate procurement, production, inventory management, logistics, distribution, information sharing, and relationships among supply-chain partners. Such technologies include enterprise resource planning (ERP), electronic procurement, warehouse-management systems, Internet of Things (IoT), radio-frequency identification (RFID), GPS and fleet-management systems, cloud computing, blockchain, digital platforms, big-data analytics, and automated inventory-management systems.

Lee et al. (2024) reported that digital supply-chain capabilities can contribute to improved operational performance. Lee et al. (2024) and Yu et al. (2024) indicated that Supply-chain analytics is particularly important because it converts operational data into information that can support forecasting, disruption identification, bottleneck analysis, and strategic decision-making. The increasing combination of analytics, IoT, AI, and cloud technologies is consequently creating more integrated digital supply-chain ecosystems

Supply Chain Technology and Manufacturing Firms

The integration of advanced supply-chain technologies has been found to transform traditional supply networks into more connected, responsive, and data-driven systems. ERP systems integrate information across organisational functions, facilitating coordinated decision-making. E-procurement systems can automate purchasing and supplier-management processes, while inventory technologies such as RFID and barcode systems improve the visibility and monitoring of materials and finished goods. GPS and fleet-management technologies can improve logistics monitoring, while cloud-based platforms facilitate information sharing across supply-chain partners. Lee et al. (2024) further indicates that digital supply-chain transformation and smart technologies can improve manufacturing performance by increasing information visibility, coordination, responsiveness, and analytical capability. Yu et al. (2024) found that technologies such as IoT and AI positively affects supply-chain performance and innovativeness. This suggests that the technology can

contribute to firm performance not only by reducing operating costs but also by strengthening the firm's capacity to withstand disruptions

Concept of Firm Value

Firm value represents the overall economic worth of a firm as perceived by investors and other capital-market participants. In corporate finance, maximising firm value is generally regarded as an important objective because it captures the wealth implications of managerial and investment decisions for shareholders

Firm value can be measured using market capitalisation, price-to-book ratio or market-to-book ratio. However, one of the most widely used market-based measures of firm value is Tobin's Q. The original q-theory of investment conceptualises Tobin's Q as the ratio of the market value of a firm's capital to the replacement cost of that capital (Tobin, 1969) Tobin's Q is preferred in the present study because it provides a market-based valuation measure that incorporates investors' assessment of the expected future economic benefits associated with a firm's assets and capabilities. It reflects the market's assessment of the firm's current assets, future earnings potential, growth opportunities, risk profile, and ability to generate sustainable economic benefits.

Artificial Intelligence, Supply-Chain Technology and Firm Value

The expected relationship between AI, supply-chain technology, and firm value is theoretically positive but conditional upon effective implementation and organisational capability. Shi et al. (2025) find that AI adoption significantly enhances enterprise value through both direct and indirect channels, with data assets serving as an important mediating mechanism. Their findings further indicate that firms with stronger managerial capabilities obtain greater value from AI investments. By implication, technological adoption does not automatically translate into economic value. Rather, value creation is likely to occur when firms possess complementary managerial, human, data, and organisational capabilities that enable technology to be effectively integrated into business processes.

The potential benefits of AI also extend to supply-chain efficiency and risk reduction. Li et al. (2025) found that AI adoption significantly reduces supply-chain risk. Results from the study identified supply-chain efficiency and resilience as important mediating mechanisms, and the risk-reduction effect is stronger among manufacturing firms.

However, the relationship between AI and firm value is not necessarily unconditionally positive. AI implementation can equally create operational and reputational risks when systems fail. Song et al. (2025) demonstrate that investors respond negatively to AI-related failures, with the magnitude of the effect varying according to the type and context of the failure. Supply-chain technology can similarly influence firm value through operational efficiency, improved responsiveness, and risk reduction. Digital supply-chain systems can improve information visibility and coordination, while AI-enabled analytics can strengthen forecasting, resilience, and disruption management.

The combination of AI and supply-chain technology may therefore generate complementary benefits. Supply-chain technologies provide the digital infrastructure for collecting, transmitting, and integrating operational information, while AI provides analytical, predictive, and decision-support capabilities thereby suggesting that consideration of AI and supply-chain technology is theoretically important.

THEORETICAL FRAMEWORK

Resource-Based View

The study is primarily anchored on the Resource-Based View (RBV). Barney (1991) argues that firms can achieve sustained competitive advantage when they possess resources that are valuable, rare, imperfectly imitable, and non-substitutable. From this perspective, AI capabilities and digital supply-chain infrastructure

can constitute strategic organisational resources when they are effectively integrated with firm-specific knowledge and complementary capabilities. Accordingly, the RBV predicts that firms possessing stronger technological capabilities should be better positioned to improve operational efficiency, respond to market changes, manage supply-chain risks, and create economic value.

The RBV therefore implies that simply acquiring AI software, ERP systems, analytics platforms, or other digital technologies does not automatically provide sustained competitive advantage. Value arises when technological resources are combined with managerial capabilities, proprietary data, skilled employees, organisational knowledge, and complementary business processes. This interpretation is consistent with Shi et al. (2025) who reported that managerial capability strengthens the value generated from AI adoption and that AI creates enterprise value partly through the accumulation and utilisation of data assets. The above affirmation aligns with the present study of firm value measured through Tobin's Q represents a market-based indicator through which investors' assessment of the firm's expected future economic benefits can be observed

EMPIRICAL REVIEW

Oyerogba et al. (2024) examined the influence of modern manufacturing technology adoption on firm value among listed manufacturing companies in Nigeria. Using secondary data from 39 listed manufacturing companies covering 2014–2021. The study employed random-effects regression and investigated technological and organisational factors associated with firm value. The findings indicate that adoption of modern manufacturing technologies is associated with firm value and that firms adopting newer manufacturing technologies demonstrate better performance. The study provides directly relevant Nigerian evidence, although its focus is on modern manufacturing technology broadly rather than specifically on AI and supply-chain technology.

Kim and Park (2021) investigated the relationship between AI adoption and firm performance using Tobin's Q and other performance measures. Their findings indicate a positive relationship between AI adoption and Tobin's Q, with the effect being particularly pronounced for augmentation-oriented AI and with value and cost effects more evident in manufacturing than service industries. Because the study was published as an Academy of Management Proceedings paper, it should be cited as conference proceedings rather than as an Academy of Management Journal article.

Shi et al. (2025) examined Chinese listed companies over 2010–2022 and found that AI adoption enhances enterprise value directly and indirectly through data assets. The study further shows that managerial capability positively moderates the value generated by AI investments. These findings are particularly relevant to the present study because they establish a direct empirical connection between AI adoption and enterprise value.

Yu et al. (2024) investigated AI-enabled manufacturing and found that AI for process automation and cognitive engagement positively influences manufacturers' planned and adaptive resilience. The study demonstrates that AI can contribute to manufacturing performance through improved organisational resilience, providing support for the argument that AI's economic effects can operate through operational and supply-chain mechanisms

Yu et al. (2024) also examined datafication in manufacturing supply chains and found that IoT and AI contribute to datafication, which positively affects supply-chain performance and innovativeness. Supply-chain resilience was found to mediate these relationships. This evidence supports the proposition that digital supply-chain capabilities can create value through both operational improvement and resilience enhancement.

Song et al. (2025) provide a complementary perspective by examining the negative valuation consequences of AI service failures. Based on 120 AI service-failure events involving listed firms, they found that AI service failures negatively affect firm value. The study demonstrates that the economic consequences of AI depend not only on adoption but also on implementation quality, reliability, and the management of technological risks

METHODOLOGY

The study adopts an ex-post facto research design because it relies on historical observations. A longitudinal panel approach was employed to combine cross-sectional observations across firms with annual observations over time. The study covers 2015–2024, producing a maximum of 100 firm-year observations for the ten sampled firms. The population comprises listed consumer-goods manufacturing companies on the Nigerian Exchange. The proposed sample consists of ten firms selected based on their classification within the consumer-goods/manufacturing sector, availability of annual reports for the study period, availability of market-price and share-outstanding information, sufficient corporate disclosure for construction of the technology indices, and continuity of listing during the principal study period. The selected firms were Champion Breweries Plc, Guinness Nigeria Plc, International Breweries Plc, Nigerian Breweries Plc, Dangote Sugar Refinery Plc, NASCON Allied Industries Plc, Cadbury Nigeria Plc, Nestlé Nigeria Plc, PZ Cussons Nigeria Plc, and Unilever Nigeria Plc. The Nigerian Exchange's 2025 equity classification places these firms within the Consumer Goods sector, including the beverages, food products, diversified food products, and personal/household products subsectors (Nigerian Exchange Group [NGX], 2025). The above companies were selected based on their relevance to the study, availability of annual reports and market data, continuity of listing, and adequacy of corporate disclosures required for constructing the study variables

The principal sources of data are the audited annual reports of the sampled firms, Nigerian Exchange historical equity information, corporate governance and sustainability reports, annual reports, corporate strategy disclosures, and other publicly available corporate disclosures.

Because artificial intelligence adoption and supply-chain technology adoption are not ordinarily reported as separate accounting line items in corporate annual reports, the study operationalises these constructs by combining disclosure-based textual indices constructed from firms' annual reports, where Research and development cost associated with supply technology serves as proxy for Supply Chain Technology (SCT), while Automation Investments for the year were considered as proxies for Artificial Intelligence. Marston and Shrives (1991) define disclosure indices as lists of selected information items that may be disclosed in corporate reports, with an aggregate score providing a measure of the extent of disclosure. Cooke (1989) equally used corporate annual reports to measure the extent of voluntary disclosure among companies.

One of the most widely used market-based measures of firm value is Tobin's Q. It is defined as the ratio of the market value of a firm's capital to the replacement cost of that capital (Tobin, 1969). Researchers generally use an approximation of the theoretical Tobin's Q because the replacement cost of assets is difficult to observe directly. One of the major advantages of Tobin's Q is that it can captures aspects of firm value that are not fully reflected in conventional accounting measures. In the Nigerian context, Tobin's Q has increasingly been employed in empirical studies to examine the determinants of firm value among listed companies, Adeyemi et al. (2024)

Result Presentation And Analysis

Table 1 **Descriptive Statistics**

Variable	Mean	Std. Dev.	Minimum	Maximum
SCT	37.06	38.24	0.38	93.11
AI	-1.01	2.05	-3.76	1.26
Tobin's Q	5.04	2.42	1.44	9.29

Table 1 presents the descriptive statistics of the study variables, namely Supply Chain Technology (SCT), Artificial Intelligence (AI), and Tobin's Q, for the sampled consumer goods companies. The results reveal considerable variation in the technological capabilities and market valuation of the companies. Supply Chain Technology (SCT) has a mean of 37.06 and a standard deviation of 38.24, with values ranging from 0.38 to 93.11. The relatively large standard deviation indicates substantial differences in the level of supply chain technology adoption among the sampled consumer goods companies. The wide range suggests that while some

companies have relatively low levels of supply chain technology adoption, others have considerably higher levels. Such differences could be variations in the use of digital supply chain systems, inventory management technologies, supply chain analytics, logistics tracking, enterprise resource planning, warehouse automation, and digital procurement systems. The variation in SCT therefore suggests that consumer goods companies differ considerably in their ability to use technology to coordinate supply chain activities, manage inventory, improve operational visibility, and respond to changes in consumer demand.

Artificial Intelligence (AI) records a mean of -1.01 and a standard deviation of 2.05, with a minimum value of -3.76 and a maximum value of 1.26. The negative mean indicates that the average value of the AI measure is below zero. However, the interpretation of this negative value depends on the methodology used to construct the AI variable. The range indicates considerable differences in AI-related capabilities or applications among the sampled consumer goods companies. These differences may reflect variations in the application of AI to demand forecasting, inventory optimization, customer analytics, production planning, predictive maintenance, pricing, logistics, and other decision-making activities. Thus, the descriptive statistics suggest that the adoption or utilization of AI is not uniform across the sampled companies.

Tobin's Q has a mean of 5.04 and a standard deviation of 2.42, with values ranging from 1.44 to 9.29 indicate considerable variation in the market valuation of the sampled consumer goods companies. The differences in Tobin's Q suggest that investors assign different values to the companies based on their expected future performance and other firm-specific characteristics. This variation provides a basis for examining whether differences in technological capabilities, particularly Supply Chain Technology and Artificial Intelligence, are associated with differences in firm value.

Table 2 **Pearson Correlation Matrix**

Variable	SCT	AI	Tobin's Q
SCT	1		
AI	0.557	1	
Tobin's Q	0.68	0.482	1

The results indicate that both Supply Chain Technology and Artificial Intelligence are positively associated with firm value among the sampled consumer manufacturing firms. SCT demonstrates the strongest correlation with Tobin's Q ($r = 0.680$), followed by AI ($r = 0.482$). Furthermore, the moderate positive correlation between SCT and AI ($r = 0.557$) indicates that the two technologies are related but do not exhibit an excessively high bivariate correlation. These findings provide preliminary evidence of a positive association between technological capabilities and firm valuation, which can be further examined using multiple regression analysis to determine whether these relationships remain after controlling for other relevant factors.

Regression Analysis

The estimated model is:

$$TQ = \beta_0 + \beta_1AIS + \beta_2SQ + \beta_3SCT + \beta_4AI + \varepsilon$$

Table 3 **Regression Results**

Variable	Coefficient	t-value	p-value
Constant	12.412	3.676	0.002
SCT	-0.101	-2.727	0.016
AI	0.651	0.848	0.41

Model Summary

Statistic	Value
R^2	0.746

Adjusted R ²	0.679
F-statistic	11.03
Prob(F-statistic)	0
Durbin-Watson	1.61

Table 3 presents the regression results examining the effects of Artificial Intelligence (AI) and Supply Chain Technology (SCT), and Artificial Intelligence (AI) on Tobin's Q among the sampled consumer manufacturing firms. The results provide evidence of varying relationships between the explanatory variables and firm value. Artificial Intelligence (AI) has a positive coefficient of 0.651, with a t-value of 0.848 and a p-value of 0.410. The positive coefficient suggests that higher levels of AI are associated with higher Tobin's Q, holding the other explanatory variables constant. This finding is directionally consistent with Kim and Park (2021), whose research links artificial intelligence with firm performance and examines the role of AI and big-data usage within digital supply-chain management. However, the present study differs in that the positive AI coefficient does not achieve statistical significance when firm value is measured using Tobin's Q. This may be explained by the possibility that the benefits of AI materialize through operational and organizational channels before being reflected in market valuation. The findings are also consistent with the broader evidence reported by Shi et al. (2025), which indicates that AI development can influence supply-chain structures through improvements in coordination and information transparency. Similarly, Song et al. (2025) provide evidence that AI can strengthen supply-chain resilience through efficiency gains, cost reductions, and improved profitability. These studies suggest that AI may create value through supply-chain efficiency and resilience rather than necessarily producing an immediate direct effect on market valuation.

Supply Chain Technology (SCT) records a negative coefficient of -0.101, with a t-value of -2.727 and a p-value of 0.016. The negative and statistically significant coefficient of Supply Chain Technology ($\beta = -0.101$, $p = 0.016$) is particularly noteworthy. This finding contrasts with the positive Pearson correlation between SCT and Tobin's Q reported in Table 2 ($r = 0.680$). The difference suggests that the simple positive association between SCT and firm value changes when other technology-related variables are held constant. This can be interpreted as a conditional relationship rather than evidence that supply chain technology inherently reduces firm value.

SUMMARY CONCLUSION AND RECOMMENDATIONS

Summary

The regression results provide mixed evidence regarding the relationship between technological capabilities and firm value among consumer manufacturing firms. Supply Chain Technology (SCT) has a statistically significant effect on Tobin's Q at the 5% level, while Artificial Intelligence (AI) did not achieve statistical significance at the conventional 5% level. These findings suggest that the relationship between technological adoption and market valuation may be more complex than a simple assumption that greater technology adoption automatically results in higher firm value.

The result aligns with Yu et al. (2024), who found that digital supply chain practices contribute to supply chain viability and operational performance and that supply chain viability plays a mediating role in the relationship between digital supply chain practices and operational performance. Their findings imply that the benefits of digital supply chain technologies may occur through intermediate operational mechanisms rather than directly through firm value.

The finding is also relevant to Oyerogba et al. (2024), who investigated the adoption of modern manufacturing technologies and firm value among listed manufacturing companies in Nigeria. He found that adoption of modern manufacturing technologies is associated with firm value and that firms adopting newer manufacturing technologies demonstrate better performance. The negative coefficient observed in the current study may therefore indicate that technological investment and operational improvement do not necessarily translate immediately into higher market valuation.

Conclusion

This study examined the relationship between Supply Chain Technology (SCT), Artificial Intelligence (AI), and firm value among consumer manufacturing firms, with Tobin's Q serving as the measure of firm value. The descriptive statistics indicate substantial variation in the adoption and utilization of Supply Chain Technology and Artificial Intelligence across the sampled firms, as well as considerable differences in firm valuation. This variation suggests that consumer manufacturing firms differ in their technological capabilities and market valuation.

The findings suggest that technological adoption among consumer manufacturing firms does not have a uniform effect on market valuation. Supply Chain Technology exhibits a statistically significant negative conditional relationship with Tobin's Q, whereas Artificial Intelligence has a positive but statistically insignificant coefficient. This contrasts with the positive bivariate relationships observed between SCT, AI, and Tobin's Q in the correlation analysis. The difference between the correlation and regression results may reflect the influence of the other explanatory variables

The study concludes that technology adoption within consumer manufacturing firms is associated with firm value, but the relationship is not uniform across technologies. Supply The findings therefore suggest that the value generated by technological investment depends not simply on the adoption of technology but also on how effectively it is integrated and converted into operational and financial outcomes.

The findings therefore contribute to the existing literature by indicating that the value implications of technological adoption may depend not only on whether firms adopt technology, but also on how different technologies interact, how effectively they are integrated into organizational processes, and the time required for their benefits to be reflected in firm valuation

Recommendations

Based on the findings of the study, the following recommendations are proposed for managers of consumer manufacturing firms, investors, policymakers, and other relevant stakeholders:

Consumer manufacturing firms should not view the acquisition of Supply Chain Technology or Artificial Intelligence as an end in itself. Rather, management should evaluate technology investments based on their expected contribution to operational efficiency, cost reduction, revenue growth, customer responsiveness, and ultimately firm value. Firms should therefore avoid expecting immediate improvements in market valuation from AI investments

Consumer manufacturing firms should therefore consider developing integrated digital infrastructures in which supply-chain technologies provide reliable, timely data that can support AI applications. This can enhance demand forecasting, inventory optimization, production planning, logistics management, and supplier coordination.

Firms should establish appropriate data governance systems, including data-quality controls, cybersecurity measures, access controls, and clear responsibilities for data management. Poor-quality or fragmented data can reduce the effectiveness of both AI and supply-chain technologies. Management should regularly assess whether technology investments are generating measurable economic benefits.

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