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Ai-Driven Supply Chain Optimization for Sustainability: Evidence from Nigeria Manufacturing Industry

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Abstract: The growing demand for sustainability in manufacturing and the inefficiencies of traditional methods in the supply chain highlight the importance of finding smarter solutions. Even with the growing availability of digital tools and AI technologies, organizations are yet to fully utilize them to aid sustainability efforts, causing inefficient use of resources, waste, and environmental damage. The chapter examined AI supply chains optimizing for sustainability: evidence from Nigeria manufacturing industry. The chapter utilized a survey research design with a population of 950 supply chain employees in Nigerian Breweries, Lagos State, with an estimated sample size of 281 using the Yamane (1967) formula. Data was collected using a structured questionnaire with a five-point Likert scale. Descriptive statistics and multiple regression analysis were used to analyze the data in SPSS version 27. The findings showed that AI-driven demand forecasting (coefficient = 4.287) and AI-based inventory optimization (coefficient = 3.549) have a positive significant on sustainability, with 56.7% of the variance in sustainability outcomes. The chapter concluded that AI-driven supply chain optimization plays a significant role in minimizing waste, optimizing resources, and meeting market demand. The study recommended that Nigerian Breweries should utilize AI-powered demand forecasting tools for production planning and should implement AI-based inventory optimization systems to ensure that inventory levels are optimized and reducing excess stock.

Keywords: Artificial Intelligence, Supply Chain Optimization, Sustainability, AI-Driven Demand Forecasting and AI-Based Inventory Optimization

1 Introduction

Manufacturing systems today are more complex, and optimized processes are now linked with highly interconnected global manufacturing and distribution systems and are dependent on system integration, agility, and efficiency. In U.S., Germany, and China, inefficiencies remain in the supply chain because there is inconsistent demand and inventory mismanagement, as well as sub-optimal operations. However, the problem of managing inventory still exists, and the loss of inventory because of overstock and stockout conditions is estimated as being approximately 20-30% of the costs of logistics globally. However, traditional supply chain management has been founded on the assumption of data trends and linear forecasting models, which are not applicable for today's market with dynamic and uncertain demand. Traditional forecasting methods that use statistical techniques do not necessarily need to adapt to the dynamic nature of the supply and demand side in a real market situation, particularly as for the choice of inventory control model to be used (Shukor et al., 2020; Sujatmiko et al., 2024).

AI is one of the drivers of next-generation supply chain optimization, which allows for the adoption of big data analytics, forecasting, and decision support in real-life situations. Developed countries like the United States, Japan, and the United Kingdom have started using AI systems in their supply chains, which have helped them improve forecasting, inventory management, and logistics operations. More specifically, machine learning algorithms are more appropriate for modeling complex demand and making early forecasts, and intelligent optimization models can help in real-time decision-making at every point along the integrated supply chain. Two important operational issues that can be impacted by AI use are demand forecasting and inventory management (Douaioui et al., 2024; Obuseh et al., 2025). Sustainability is now a core component of production chain management because of the necessity to minimize waste and make efficient use of resources. Even if the degree of input and resource waste in production processes is low, the economic and environmental damage continues to be large, and it is estimated that some industries suffer more than 25%

of input and resource waste in production processes, according to studies. Poor demand forecasting and stock control (overproduction and spoilage) practices and unnecessary build-up of stocks (Agata, 2024) compound the inefficiency of resource utilization and the waste of resources.

AI's integration into supply chain processes provides a structured approach to tackle sustainability issues via improved efficiency. Accurate forecasting prevents overproduction, which reduces the wastage of raw materials, and effective inventory control practices minimize wastage due to poor inventory control and spoilage (Meghana & Ekaterina, 2025). These are in direct support of key sustainability goals in terms of efficiency in resource use and waste management. The adoption of new digital technologies for the supply chain is still low, and where it is being used, it is in Sub-Saharan Africa, specifically South Africa and Kenya, where logistics and manufacturing are being digitalized. As seen in Nigeria, there are structural problems in the manufacturing sector, such as forecasting, inventory management and inter-functional coordination. Although a very important sector for the country's growth and development, the sector is still not well connected with technology, and many businesses are still going on with manual or semi-automated processes for the most important activities in its supply chain (Umam, 2025; Atieh et al., 2025). The use of AI in the supply chain of advanced economies is prevalent, but Nigeria's manufacturing industry especially Nigerian Breweries in Lagos State, has limited use on how it is applied in the industry (Okereke et al., 2025). Most of the previous studies have been on digital transformation or overall supply chain performance but lack emphasis on sustainable practices with AI, such as demand forecasting and inventory optimization and their relation to sustainability performance. It is on this gaps that this chapter lies upon, Furthermore, this chapter examine how AI demand forecasting and AI-based inventory optimization can help achieve sustainability at Nigerian Breweries in Lagos State.

2 Literature Review

According to Huang and Peissl, AI is the development of systems capable of independently understanding sensory information and learning from it to make decisions that yield successful results. Peretz-Andersson et al. (2024) explain that AI is a system's ability to perceive its surroundings and adapt based on them, allowing the system to continually refine its decision-making processes and optimize its chances of success over time. AI is renowned for its ability to process large amounts of data, identify meaningful patterns, and make predictions from data that might not be apparent from traditional data analysis techniques. One of these capabilities of AI is its “learnability” from data, which makes it most suitable for complex and dynamic environments (Shukor et al., 2020). Nwangwu et al. (2025) explain that AI can aid organizations in managing complex and dynamic systems, identifying patterns and relationships that might otherwise go unnoticed. AI can be especially beneficial in other industries, such as manufacturing, where it can be employed to optimize operations and make informed decisions on-the-fly, for example, by predicting demand needs or managing inventory. AI enhances system coordination and responsiveness by synthesizing data from multiple sources, allowing enterprises to make well-informed and prompt decisions (Umam, 2025). AI is integral to forecasting customer requirements, maximizing resources, and boosting efficiency, signaling a more data-driven and intelligent decision-making process across various sectors.

2.1 AI-Based Inventory Optimization

Mohamed (2024) defines inventory management as managing inventory to get resources on time and to minimize inventory holding and ordering costs. One of the challenges is dealing with stocking problems like overstocking or running out of stock. Overstocking leads to an increase in storage expenses, capital binding, and wastage (Mweshi, 2022), while stockouts result in production failures, delays, and service level issues (Nwangwu et al., 2025). Khan et al. (2025) state that uncertainty and volatility in demand make the problem of inventory control difficult because of the fixedness of the inventory in optimizing the level of inventory. The benefit of the AI systems is that they can aid in maintaining a well-balanced stock of goods with the demand without wasting anything, (Sánchez et al., 2020). Okafor et al. (2025) contend that machine learning enhances inventory management by learning from past patterns of demand and responding to demand variability. Negri et al. (2021) state that AI can assist in forecasting demand for inventory and replenish it in time without overspending or running out of stock. Using AI, the system determines reorder points and lead times for the correct inventory management.

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2.2 AI-Driven Demand Forecasting

Demand forecasting has been recognized as one of the important components of supply chain management in the manufacturing system where the production is planned based on the demand. Vikas et al. (2021) explain that demand forecasting is the ability to forecast the demand of a product, and Masa'deh et al. (2022) note that the principle of demand forecasting is that it is crucial to synchronize the supply and demand by predicting the demand of a product based on previous data and other factors. Predicting manufacturing requires multiple difficulties, some of which involve the variability of product demand, such as seasonality, market fluctuations, economic variables, and consumer behavior. However, traditional methods are not flexible or comprehensive enough to make more accurate predictions, as Arora (2024) stated, and Dhal and Kar (2024) posits that AI-based models can offer a more flexible and information-rich approach to forecasting. Demonstrating that these algorithms, particularly machine learning models, can adapt and evolve over time by learning from previous and current data to enhance prediction accuracy. According to Onukwulu et al. (2023), the use of AI models provides information that is outside of the forecasting system, such as environmental factors, market dynamics, and consumption patterns, which can complement the demand forecast.

2.3 Sustainability

According to Thun et al. (2024), sustainability is "economic, environmental, and social performance, combined in the activities of a business," and Sánchez-Flores et al. (2020) define sustainability in supply chains as the "effective management of material and information flows so as to be efficient in the long term without exhausting the resources." In the manufacturing environment, sustainability is associated with production inputs and processes being managed efficiently. The efficient use of resources is one of the important aspects in operation, and material efficiency is a major reason for material wastages and inefficiency in most manufacturing operations, as stated by Okereke et al. (2025) and Negri et al. (2021) argue that inefficient planning, particularly customer order forecasting and inventory management, is the major cause of material wastages and inefficiency.

2.4 The Use of Artificial Intelligence in Supply Chain Management

In the research literature, AI is one of the disruptive technologies in today's supply chain, especially for manufacturing systems that operate in an uncertain and complex environment. AI can optimize supply chain activities by enabling data-driven decision-making (Khokrale, 2025). Current supply chain approaches are dependent on the past and the involvement of people and are under strain in highly variable and unpredictable environments. In this context, Okafor et al. (2025) state that AI brings increased visibility, coordination, and agility by processing vast amounts of structured and unstructured data to deliver predictive insights. Good production planning and resource allocation can be achieved by using better forecasts (Shukor et al., 2020), while complex demand patterns can be captured by applying machine learning algorithms (Neira and Angel, 2024). Furthermore, Rashid (2022) argues that predictive analytics helps in making proactive decisions as a prediction of disruption and reduction of operational costs. In terms of inventory management, AI can be used to track inventory in real-time, minimizing overstocking and stockouts.

2.5 Theoretical Review

The chapter is based on the Resource Based View (RBV) theory developed by Birger Wernerfelt (1984) and developed by Jay Barney (1991). The RBV states that the competitive advantage is able to be sustained as long as the firms have valuable, rare, inimitable, and non-substitutable (VRIN) resources. The theory is based on the premise that there is a non-uniform allocation of firm resources/capabilities, and even the variation in firm performance can be attributed to the same phenomenon (Atieh et al., 2025). This perspective sees the force of the firm, such as AI technologies, as a strategic asset that will enable the firm to be more efficient and effective. In this study, the capability of the firm's use of information, decision-making, and resource allocation are identified as critical firm capabilities that can help the firm use AI to improve demand forecasting and inventory optimization. The skills are intended to help increase the sustainability outcome by eliminating the inefficiencies of overproduction and overstocking, as well as by planning, which in turn reduces resources wasted and better uses of resources. The RBV thus offers a good reason why the application of AI-based systems could contribute to improved sustainability outcomes in manufacturing supply chains, especially where there is complexity, as in Nigerian Breweries. The critics of the theory, however, state that its attention is not sufficient towards environmental factors and it is static, meaning that it does not consider the market and the technological innovations that may occur over time (Thun et al., 2024; Hassan, 2024).

3 Empirical Studies

Shukor et al. (2020) examined the effect of environmental uncertainty and organizational ambidexterity on the integration of supply chains and the connection between supply chain agility and organizational flexibility among manufacturing companies. The data were collected from 526 managers of services and manufacturing industries in Kuala Lumpur. The approach in this research is by using the software of partial least squares (SmartPLS 3.0) based on the structural equation modeling (SEM) technique. The results revealed that there is a high correlation between integrating with customers and suppliers and integrating with the internal systems and uncertainty in their environment. There is a significant relationship between organizational ambidexterity and integration of the supply chain. Results indicated a positive impact of integration in the supply chain for the company's agility and flexibility in the supply chain.

Hassan (2024) examined the factors influencing the adoption of AI in Nigeria's supply chain industry. The quantitative research approach was used in this research in order to examine the drivers of artificial intelligence (AI) in the Nigerian SCM sector. Data collected were quantitative data from 80 respondents of the local supply chain practitioners, from which quantitative data was obtained and subjected to data analysis using statistical tests. This study showed that several factors such as the support and leadership of the senior management, the technological infrastructure, and regulations and regulatory considerations, among others, are the most important factors that contribute to the adoption of AI in Nigeria's supply chain management. The result of the study is applicable to the policymakers, practitioners, and researchers. It has also urged the creation of an enabling environment for the use of AI and regulatory clarity and technological skills development to harness the potential of AI in the Nigerian supply chain management sector.

Nwangwu et al. (2025) carried out research on the adoption of artificial intelligence (AI) and decision-making in the supply chain management of lubricant companies in Anambra State in Nigeria. The concept of technology acceptance theory (TAT) was used for the study. A questionnaire was developed for the study. The total population of the study was made up of 13 lubricant companies in the entire Anambra State with two hundred and eighty-one (281) management staff. The 269 were filled, and the returned data was analyzed using a computer program, SPSS version 23, based on a correlation analysis. The findings of this study showed that: Based on the result of this study, it is concluded that machine learning is one of the important parameters that affects the decision support system (DSS) of the lubricant firms in Anambra State, Nigeria ($T=2.244$, $P=0.006$). The effect of neural networks on the creative decision skills of the lubricant firms in Anambra State is significant ($T=9.790$ and $P=0.009$). The study has shown that predictive analytics (AI) has enhanced the decision making in the supply chain of the lubricant firms to Anambra state Nigeria. The research reveals that businesses need to be focused on collecting, storing and analysing data. Special knowledge is needed for the algorithm of neural networks to be set up and optimized. Employing experts or training employees is recommended.

Umam (2025) examined the use of AI for logistics and supply chain optimization and its impact on local development. The study is conducted using mixed-method data, with qualitative data analyzed using thematic analysis to get the challenges of MSME actors and perceptions, while quantitative data is analyzed descriptively for the effect of the study in enhancing logistics efficiency. It was found that the use of AI can enhance inventory management and route planning and can decrease the cost of distribution up to 20%. But the cost of implementing AI and inadequate technological infrastructure are still challenges for MSMEs to adopt AI. The recommendations from this study involve financial support from the government and capacity development training for MSMEs to empower them to address these challenges and make use of AI to drive economic development in the region. The study recommends subsidies, training in AI technology, and grants on technology to the MSMEs by the government for availing the AI technology in their supply chain.

Obuseh et al. (2025) examined the leverage artificial intelligence (AI) can offer to supply chain risk management (SCRM) and improve trade in Southeast Nigeria. The research design adopted was quantitative; the respondents were 400 supply chain professionals, logistics managers, and SME operators in 5 states in the southeast region. Descriptive statistics, Pearson correlation, and multiple regression (SPSS version 26) were used for data analysis. Results indicated there was a positive and significant correlation between the adoption of AI and operational risk mitigation, resilience, and the efficiency of trade in the supply chain at $p < 0.001$. Results have validated the capabilities of AI-powered technologies like predictive analytics, real-time monitoring, and autonomous decision support as dynamic capabilities that can enhance responsiveness, resilience, and competitiveness under risky trading situations. The study's findings have implications for managers who are making decisions on whether to invest in supply chain solutions that incorporate AI and for policymakers who want to create guidelines around digital skills and ethical AI regulations to foster adoption and to establish a harmonization of regulations.

4 Methodology

In this study, survey research design was adopted. The study population is made up of 950 supply chain employees at Nigerian Breweries in Lagos State, Nigeria. They were selected because they engage in activities in the supply chain such as forecasting and managing stock and thus have knowledge about the study variables and can provide valid information. Yamane's formula (1967) was used to determine the sample size of 281 at a 5% level of precision. The sampling technique used in this study was the purposive (judgmental) sampling technique, in which the respondents were selected based on their suitability in the study. In this way only those with enough expertise in the process can be selected to participate in the chain, thereby increasing the quality and integrity of the data. A questionnaire was developed to collect the data to meet the constructs of the study. A 5-point Likert scale was used to develop the questionnaire with the following responses: 1 = Strongly Agree, 2 = Agree, 3 = Neutral, 4 = Disagree, and 5 = Strongly Disagree. For the clarity and relevance of the questionnaire, the face and cotent validity of the questionnaire was assessed. To measure the reliability of the questionnaire, the Cronbach's alpha coefficient was computed, and the value was more than 0.70, which shows that the questionnaire is reliable. Data was analyzed by using the Statistical Package for the Social Sciences (SPSS) 27. Data were analyzed using descriptive statistics (frequency, mean, and standard deviations), and the inferential statistics were done to test the hypotheses. Ethical issues were adhered to in the study. The anonymity and confidentiality of the respondents' answers were respected, and the respondents had the right to participate, and the information collected was voluntary and informed.

Data Analysis, Discussion and Presentations

Table1: Summary of Questionnaire Distribution and Response

Number of distributed questionnaires	Number of completed questionnaires	Number of incomplete questionnaires	Response rate
281	278	3	98.9%

Source: Author’s Fieldwork Computation, (2026)

Table 1 shows that 281 questionnaires were distributed to the respondents. Of these, 278 (98.9%) were completed and returned, with 3questionnaires was not returned.

Demographic Profile of the Respondents

Table 2: Demographic Profile of Respondents (n = 278)

Variable	**Category**	**Frequency**	**Percentage (%)**
Gender	Male	198	71.2
	Female	80	28.8
	Total	**278**	**100.0**
Age (Years)	20 – 29	54	19.4
	30 – 34	126	45.3
	35 – 44	64	23.0
	45 and above	34	12.2
	Total	**278**	**100.0**

Qualification	OND/NCE	62	22.3
	HND/B.Sc	216	77.7
	Total	**278**	**100.0**
Experience (Years)	1 – 5	82	29.5
	6 – 10	124	44.6
	11 – 15	48	17.3
	Above 15	24	8.6
	Total	**278**	**100.0**

Source: Author's Fieldwork Computation, (2026)

The study surveyed a total of 278 respondents. In terms of gender distribution, the majority were male (71.2%), while females constituted 28.8%, indicating a predominantly male sample. Regarding age, the respondents were largely concentrated in the 30–34 years category (45.3%), followed by the 35–44 years group (23.0%) and 20–29 years (19.4%), with a smaller proportion aged 45 and above (12.2%). This suggests that the sample was predominantly middle-aged adults, with a substantial representation of early-career professionals. In terms of educational qualifications, most respondents held HND/B.Sc degrees (77.7%), whereas a smaller proportion had OND/NCE qualifications (22.3%). This indicates that the majority of the participants possess higher education qualifications, which may influence their knowledge, perception, and engagement with the study variables. For work experience, the largest group of respondents had 6–10 years of experience (44.6%), followed by 1–5 years (29.5%), 11–15 years (17.3%), and above 15 years (8.6%). This distribution reflects a workforce with a mix of early-career and moderately experienced individuals, with fewer respondents having long-term experience exceeding 15 years.

Table 3: Descriptive Statistics of the Respondents' Perceptions Based on Variable Questions

Variables	N	Minimum	Maximum	Mean	Std. Deviation
AI-Driven Demand Forecasting	278	2	5	4.12	0.683
AI-Based Inventory Optimization	278	2	5	4.05	0.721
Sustainability	278	2	5	4.18	0.647

Source: Author's Fieldwork Computation, (2026)

Table 3 shows descriptive statistics of the respondents' perception of AI-driven demand forecasting, AI-based inventory optimization, and sustainability in Nigerian Breweries in Lagos State, Nigeria. The mean score for AI-powered demand forecasting was 4.12 (SD = 0.683), ranging from 2 to 5, which means that the respondents generally agreed that there was a good use of AI for demand forecasting. Likewise, the average score among the respondents for AI for inventory optimization is 4.05 with a standard deviation of 0.721, indicating that AI is seen as valuable in inventory management and enhancing operational efficiency. Sustainability had the highest mean score (4.18) and standard deviation (0.647), pointing to high agreement that sustainability is efficiently used.

Test of Hypotheses

Table 4 Multiple Regression Results: AI-Driven Supply Chain Optimization for Sustainability in the Nigerian Manufacturing Industry

Variable	Unstandardized Coefficient (B)	Std. Error	t-value	Sig. (p)
Constant	-9.482	5.421	-1.75	0.082
AI-Driven Demand Forecasting	4.287	0.912	4.70	0.000
AI-Based Inventory Optimization	3.549	0.887	4.00	0.000

Source: SPSS Output (2026)

Model Statistics:
$R = 0.753$
$R^2 = 0.567$
Adjusted $R^2 = 0.557$
$F (9, 378) = 47.631$***
Durbin–Watson = 1.512
Std. Error of Estimate = 0.4374

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***$p < 0.01$, **$p < 0.05$, *$p < 0.10$
Dependent Variable: Sustainability

5 Findings

Table 4 reveals that there is a positive and statistically significant relationship between both AI-driven demand forecasting and AI-based inventory optimization with sustainability. The R^2 value of 0.567 shows that the independent variables in this model explain 56.7% of the variance of the sustainability results. One can easily see that the application of AI optimization tools in manufacturing has a tremendous impact on the aspect of sustainability. The results of the study indicate that the most important factor affecting the sustainability is the AI-based demand forecasting (coefficient – unstandardized: 4.287; t value: 4.70 ($p<0.000$)). This means that by accurately predicting what customers are likely to want, AI can help manufacturers better meet customer demand, reducing waste and wasteful consumption and thereby increasing sustainability. Predictive demand forecasting allows manufacturers to avoid overproduction, reduce material waste, save on energy consumption, and use their operations more efficiently to become more sustainable. Furthermore, the coefficients of positive influence with inventory optimization based on AI on sustainability are unstandardized, and the t-value is 4.00 ($p < 0.000$), indicating that the influence of inventory optimization based on AI on sustainability is very strong. This means AI optimization of inventory improves resource management, decreasing overproduction of raw materials and waste along the manufacturing process. With no overstocking and no waste, inventory management is also an important factor to support manufacturers in achieving their sustainability goals. The value of the Durbin-Watson statistic is 1.512, which is a positive sign for the regression model because there is no significant autocorrelation among the residuals.

6 Discussion of Findings

The result showed that the most powerful driver of sustainability is AI-driven demand forecasting, which had a coefficient of 4.287. This indicates that when manufacturers are able to accurately predict demand, they can make corresponding adjustments and reduce the risk of overproduction and material waste. Environmental inefficiencies cause wasted resources and increased carbon footprints as a result of overproduction. AI can also enhance manufacturing processes to be more efficient, thereby helping to lower resource usage and boost sustainability. The results are in line with Shukor et al. (2020), who pointed out that demand forecasting, particularly through the application of AI, plays a key role in reducing material waste and addressing customer demand, thereby fostering sustainability. Similarly, Nwangwu et al. (2025) state that accurate demand forecasting is crucial for optimizing production and minimizing waste, this is in line with the study findings that AI can play a significant role in improving sustainability in production processes. Moreover, Hassan (2024) demonstrated the potential of AI tools for forecasting food demand can aid in production matching consumer demand, thereby minimizing overproduction and material waste.

The coefficient of 3.549 shows that AI-driven inventory optimization is also relevant for enhancing sustainability. This is where AI technologies are helping manufacturers to use their resources and avoid waste. By minimizing the amount of stock needed, AI inventory optimization helps to cut down on storage expenses and the environmental footprint of having too much inventory. This is in line with the findings of Umam (2025), which are that effective inventory management also helps to minimize waste. The impact of AI-powered stock optimization on sustainability is directly linked, as it helps to avoid overstocking and depletion of resources. This aligns with the study by Obuseh et al. (2025), which demonstrated that AI-driven systems can help optimize resource utilization and directly mitigate waste and promote sustainability. In addition to this, Sujatmiko et al. (2024) stated that AI can help optimize inventory, thereby increasing efficiency and reducing overproduction and waste, which is one of the ways in which AI helps producers manage their inventory and demand, thereby improving their sustainability outcomes.

7 Conclusion and Recommendations

In conclusion, the results of this study reveal the pivotal role that AI-driven demand forecasting and AI-informed inventory optimization play in optimizing sustainability in Nigerian Breweries, Lagos State. Based on the results of regression analysis, both variables are significant in terms of sustainability, with the AI-based inventory optimization variable being the most significant. The results of this study show that the use of AI optimization methods for the supply chain can play a significant role in manufacturers' efforts towards sustainability. AI technologies are being marketed towards manufacturers to enhance sustainability.

Based on the study findings, the following recommendations were made:

I. Nigerian Breweries should utilize AI-powered demand forecasting tools for production planning and aligning production needs with actual market demand. This will minimize waste, maximize use of resources, and help to be sustainable.
II. Nigerian Breweries should implement AI-based inventory optimization systems to ensure that inventory levels are optimized, reducing excess stock, minimizing waste, and enhancing sustainability.

Managerial Implication

This study's findings are relevant to the managers of Nigerian Breweries, Lagos State. The results demonstrate the possibilities of AI-based demand forecasts and AI-based inventory optimizations for enhancing sustainability. These technologies provide opportunities to manufacturers to be more efficient, to eliminate waste, and to maximize the use of resources, improving sustainability. Managers should invest in AI-powered demand forecasting systems that are capable of precisely forecasting demand and matching production with market requirements. That will help prevent overproduction and waste, thereby contributing to the manufacturer's improved sustainability. Likewise, inventory optimization systems should also evolve towards AI, where it will optimize inventory levels and resources.

8 Limitations

The study has a number of strengths and weaknesses. The study was carried out in the manufacturing sector of the Nigerian situation; therefore, the results of the study may not be transferable to other sectors in the country and other regions of the country with different dynamics. Nigeria's manufacturers' problems could be other than those faced in other countries. Moreover, this study used structured questionnaires, which may introduce bias such as recall bias and social desirability bias. Further research is required to explore other methods of data gathering and to explore how these impacts on sustainability can be better measured through a longitudinal approach.

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