Artificial Intelligence and Managerial Decision-Making in Manufacturing Firms in Delta State

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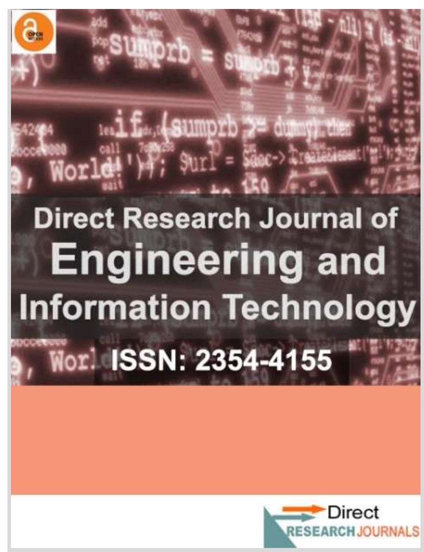
ABSTRACT

This study examined the impact of artificial intelligence (AI) on managerial decision-making in manufacturing firms in Delta State, Nigeria, focusing on machine learning and robotic process automation (RPA). A quantitative cross-sectional survey design was adopted, and data were collected from 234 managers and supervisors using structured questionnaires. The data were analyzed using descriptive statistics, Pearson correlation, and multiple regression analysis. Findings revealed that machine learning significantly enhances managerial decision-making by improving data analysis, forecasting accuracy, and decision quality. Similarly, RPA positively influences decision-making by automating routine tasks, ensuring data accuracy, and providing real-time operational insights. The regression results indicated that both variables significantly predict managerial decision-making effectiveness. The study concludes that AI technologies are critical for improving decision speed, accuracy, and strategic responsiveness in manufacturing firms. It recommends that firms invest in AI infrastructure and integrate AI tools into managerial processes to enhance performance and competitiveness. This study contributes to knowledge by providing empirical evidence on AI-driven decision-making in the Nigerian manufacturing sector.

Keywords: *Artificial Intelligence, Machine Learning, Robotic Process Automation, Managerial Decision-Making, Manufacturing Firms*



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INTRODUCTION

In the contemporary business environment, artificial intelligence (AI) has emerged as a transformative force, reshaping how organizations operate, compete, and make strategic decisions. AI refers to the development of computer systems capable of performing tasks that typically require human intelligence, including problem-solving, pattern recognition, and predictive analytics (Russell & Norvig, 2021). In manufacturing firms, AI tech-

-nologies such as machine learning, robotics, and advanced analytics are increasingly being adopted to improve operational efficiency, reduce costs, and enhance product quality (Davenport & Ronanki, 2018). Managerial decision-making in manufacturing contexts is inherently complex, involving the integration of large volumes of operational, financial, and market data to make timely and accurate choices. Traditional decision-making approaches often rely on intuition and historical experience, which may be insufficient in the face of dynamic market conditions and technological disruptions (Shrestha et al., 2019). The integration of AI tools into managerial processes provides managers with data-driven insights, predictive forecasts, and real-time operational monitoring, enabling more informed, objective, and strategic decisions (Brynjolfsson & McElheran, 2019).

In Delta State, Nigeria, manufacturing firms operate in a highly competitive environment characterized by evolving consumer demands, resource constraints, and technological advancements. The adoption of AI in managerial decision-making has the potential to enhance operational efficiency, optimize supply chain management, and improve overall firm performance. Despite these prospects, empirical evidence on the impact of AI on managerial decision-making in the Nigerian manufacturing sector remains limited, highlighting a critical research gap. This study, therefore, seeks to investigate the relationship between artificial intelligence adoption and managerial decision-making in manufacturing firms in Delta State, aiming to provide insights that can inform policy, managerial practice, and technological investment.

Study Problem

In the modern manufacturing sector, managers are faced with increasingly complex decisions due to dynamic market conditions, technological advancements, and growing operational data. Traditional decision-making methods, which rely heavily on intuition, past experience, and limited data, are often inadequate for addressing challenges such as production inefficiencies, supply chain disruptions, and fluctuating consumer demands (Shrestha et al., 2019). As a result, manufacturing firms in Delta State struggle to maintain competitiveness, optimize resource utilization, and make timely, informed strategic decisions. Artificial intelligence (AI) has emerged as a promising solution, offering capabilities such as predictive analytics, process automation, and real-time data processing to support managerial decision-making (Davenport & Ronanki, 2018). Despite its potential, the adoption and integration of AI in managerial decision-making within Delta State's manufacturing firms remain limited and uneven. There is a lack of empirical evidence on how AI tools influence decision quality, speed, and effectiveness in this specific context. This gap raises critical questions: To what extent does AI enhance managerial decision-making in Delta State's manufacturing firms? How the use of AI in decision does processes impact operational efficiency and overall firm performance? Addressing these questions is essential for providing practical insights that can guide managerial practices, policy formulation, and technological investments in the manufacturing sector.

Research Questions

i. what is the effect of machine learning on managerial decision-making in manufacturing firms in delta state?
ii. what is the effect of robotic process automation (RPA) on managerial decision-making in manufacturing firms in delta state?

Objectives of the Study

i. determine the effect of machine learning on managerial decision-making in manufacturing firms in delta state
ii. evaluate the effect of robotic process automation (RPA) on managerial decision-making in manufacturing firms in delta state

Hypotheses

H_{01}: there is no significance effect between machine learning and managerial decision-making in manufacturing firms in delta state

H_{02}: there is no significance effect between machine learning and managerial decision-making in manufacturing firms in delta state

LITERATURE REVIEW

Artificial Intelligence

Artificial Intelligence (AI) refers to the branch of computer science that focuses on creating systems capable of performing tasks that normally require human intelligence, such as learning, reasoning, problem-solving, perception, and decision-making (Russell & Norvig, 2021). AI technologies enable machines to analyze large volumes of data, recognize patterns, make predictions, and provide decision support with minimal human intervention.

In organizational contexts, particularly in manufacturing, AI is deployed to improve operational efficiency, optimize resource utilization, automate routine processes, and enhance managerial decision-making (Davenport & Ronanki, 2018). AI encompasses various subfields, including machine learning, predictive analytics, natural language processing, and robotic process automation, which collectively allow organizations to leverage data for strategic advantage. By integrating AI into managerial processes, firms can reduce human error, respond more effectively to dynamic market conditions, and make evidence-based decisions that enhance performance (Shrestha, Ben-Menahem, & von Krogh, 2019).

Managerial Decision-Making

Managerial decision-making refers to the process by which managers identify, evaluate, and choose the best course of action from available alternatives to achieve organizational objectives (Robbins & Coulter, 2021). It involves the systematic analysis of information, assessment of risks, and consideration of both internal and external factors affecting organizational performance. Effective managerial decision-making enables organizations to respond to dynamic market conditions, optimize resource utilization, and sustain competitive advantage (Simon, 1997). In contemporary organizations, the decision-making process has been increasingly supported by technological tools and data-driven insights, including artificial intelligence, which enhances the speed, accuracy, and quality of decisions (Shrestha, Ben-Menahem, & von Krogh, 2019). In manufacturing firms, managerial decisions encompass areas such as production planning, supply chain management, quality control, and human resource allocation, all of which are critical for operational efficiency and profitability.

Manufacturing Firms in Delta State

Manufacturing firms are business organizations engaged in the production of goods through the transformation of raw materials into finished products, which are then distributed for consumption or further processing (Heizer, Render, & Munson, 2017). These firms play a critical role in economic development by generating employment, contributing to gross domestic product, and fostering industrialization. In the context of Delta State, Nigeria, manufacturing firms operate across various sectors, including agro-processing, food and beverages, chemical production, and light engineering. These firms are characterized by structured production processes, reliance on skilled labor, and the adoption of technologies to improve efficiency and product quality (Obi & Okwu, 2020). The performance and competitiveness of these firms are influenced by managerial decisions, operational strategies, and the adoption of innovative technologies such as artificial intelligence to optimize production, supply chain, and quality control processes. Given the competitive and dynamic industrial environment in Delta State, manufacturing firms are increasingly leveraging data-driven and technology-enabled decision-making tools to improve operational efficiency, reduce costs, and enhance overall organizational performance (Adeoti & Akinbode, 2021).

Machine learning and managerial decision-making in manufacturing firms

Machine learning (ML), a subset of artificial intelligence, refers to algorithms and models that enable systems to learn from data, identify patterns, and improve decision-making over time without explicit programming (Russell & Norvig, 2021). In manufacturing firms, ML plays a critical role in enhancing managerial decision – making by providing predictive insights, optimizing production processes, and supporting real-time operational adjustments. Through ML applications, managers can analyze vast amounts of operational, financial, and market data to forecast demand, anticipate equipment failures, and identify bottlenecks in production processes (Davenport & Ronanki, 2018). This data-driven approach reduces reliance on intuition and manual analysis, allowing managers to make faster, more accurate, and evidence-based decisions. For instance, predictive maintenance models powered by ML can alert managers to potential machine breakdowns before they occur, enabling timely interventions that reduce downtime and costs (Shrestha, Ben-Menahem, & von Krogh, 2019).

Moreover, ML facilitates strategic and tactical decision-making by uncovering hidden patterns in production efficiency, inventory utilization, and supply chain performance. By leveraging these insights, manufacturing managers can optimize resource allocation, improve product quality, and enhance overall organizational performance. Empirical studies indicate that the integration of ML into managerial processes is strongly associated with improved decision quality, reduced operational risks, and higher competitiveness in manufacturing firms (Brynjolfsson & McElheran, 2019).

Robotic process automation (RPA) and managerial decision-making in manufacturing firms

Robotic Process Automation (RPA) refers to the use of software robots or “bots” to automate repetitive, rule-based tasks, thereby reducing human intervention and operational errors (Aguirre & Rodriguez, 2017). In manufacturing firms, RPA enhances managerial decision-making by providing accurate, timely, and standardized data from operational processes, allowing managers to focus on strategic and analytical tasks rather than routine administrative activities (Lacity & Willcocks, 2016). Through RPA, managers can access real-time information on production schedules, inventory levels, supply chain operations, and quality control processes. This automation facilitates faster and more informed decisions, as critical operational data are continuously collected, processed, and made available for analysis (van der Aalst et al., 2018). For example, RPA can automatically generate performance reports, track production delays, and flag anomalies in workflow processes, enabling managers to implement corrective actions promptly. Empirical studies indicate that firms adopting RPA experience enhanced operational efficiency, reduced costs, and improved decision accuracy. By minimizing manual errors and accelerating information flow, RPA strengthens managerial decision-making capacity, supports evidence-based strategies, and enhances overall organizational performance in manufacturing contexts (Aguirre & Rodriguez, 2017; Lacity & Willcocks, 2016).

Theoretical Review

Artificial Intelligence and Managerial Decision-Making

A suitable theory to underpin the study on Artificial Intelligence and Managerial Decision-Making is the Technology Acceptance Model (TAM), developed by Davis (1989). The TAM posits that the adoption and utilization of technology in organizations are primarily influenced by perceived usefulness and perceived ease of use. Perceived usefulness refers to the degree to which a user believes that using a particular technology will enhance job performance, while perceived ease of use reflects the extent to which the user expects the technology to be free from effort. In the context of manufacturing firms, AI technologies—such as machine learning, predictive analytics, and robotic process automation—can improve the efficiency and accuracy of managerial decision-making. By providing timely insights, reducing human error, and enabling data-driven forecasts, AI enhances managers perceived usefulness of technological tools for operational and strategic decisions (Shrestha, Ben-Menahem, & von Krogh, 2019). Similarly, when AI systems are user-friendly and integrate seamlessly with existing workflows, managers are more likely to adopt these tools for decision-making processes (Davis, 1989).

The relevance of TAM to this study lies in its ability to explain why manufacturing managers in Delta State may accept or resist AI adoption. The model helps to frame the investigation of how AI tools influence managerial decision-making by linking technological characteristics (predictive capabilities, automation, and analytics) with managerial behavior and performance outcomes. For instance, managers who perceive AI as enhancing decision accuracy and reducing operational risks are more likely to incorporate AI-driven insights into production planning, quality control, and supply chain management. Furthermore, TAM provides a theoretical lens to explore how factors such as technological infrastructure, managerial competence, and organizational culture moderate the relationship between AI adoption and managerial decision-making effectiveness (Venkatesh & Bala, 2008). This aligns with the study's objectives of examining the impact of AI sub-variables, such as machine learning, predictive analytics, and robotic process automation, on managerial decision-making in manufacturing firms in Delta State.

Empirical Review

Davenport and Ronanki (2018) conducted a study examining the adoption of artificial intelligence in organizations and its impact on managerial decision-making. The study employed a mixed-methods approach, including surveys of 150 managers in manufacturing and service sectors, alongside in-depth interviews with 20 senior executives. The findings revealed that AI applications, particularly machine learning and predictive analytics, significantly improved managerial decision-making by providing actionable insights derived from large datasets. Managers reported enhanced operational planning, reduced errors in resource allocation, and more accurate forecasting of production demands. The study also highlighted that AI-enabled decision support systems helped managers identify inefficiencies in supply chains and optimize production schedules. Importantly, the research indicated that the effectiveness of AI adoption depended not only on technological infrastructure but also on managerial competence and organizational culture. Managers who were trained to interpret AI-generated outputs made more informed and timely decisions, whereas organizations lacking technical expertise struggled to integrate AI insights into daily decision-making processes. The study concluded that AI has a transformative effect on managerial decision-making, improving both strategic and operational performance. This finding is relevant for manufacturing firms in Delta State, where adopting AI could enhance production efficiency, reduce operational risks, and support evidence-based managerial decisions.

Shrestha, Ben-Menahem, and von Krogh (2019) investigated how artificial intelligence affects organizational decision-making structures in manufacturing firms. The study utilized a survey design targeting 220 managers and supervisors in medium- and large-scale manufacturing companies across emerging markets. The results revealed that AI tools, including robotic process automation, predictive analytics, and natural language processing, facilitated faster and more accurate managerial decisions by providing real-time operational insights. Managers were able to monitor production performance, predict equipment failures, and optimize workforce allocation. The study also found that AI integration strengthened strategic planning by reducing uncertainty and improving scenario analysis, which enabled managers to respond proactively to market and operational challenges. Furthermore, organizations that invested in AI training and data infrastructure experienced higher managerial confidence and decision quality. However, the study noted that challenges such as resistance to change, inadequate technical skills, and poor data governance could limit AI's effectiveness. The findings underscore the importance of combining technology adoption with capacity-building initiatives to maximize managerial decision-making efficiency. For manufacturing firms in Delta State, these insights suggest that AI adoption can enhance operational performance, reduce errors, and provide a competitive advantage in a rapidly evolving industrial environment.

METHODOLOGY

Research Design

This study adopted a quantitative research design using a cross-sectional survey approach to examine the relationship between artificial intelligence (AI) adoption

Table 1: Sample Distribution of Respondents

Manufacturing Firm Category	Total Population	Sample Size (n)
Agro-processing	180	75
Food and Beverage	140	59
Chemical Manufacturing	120	50
Light Engineering	120	50
Total	560	234

and managerial decision-making in manufacturing firms in Delta State. A quantitative design is appropriate because it allows for the measurement of relationships between AI sub-variables, such as descriptive analytics and diagnostic analytics, and the dependent variable, managerial decision-making (Creswell & Creswell, 2018). The cross-sectional survey design enables the collection of data at a single point in time from managers and supervisors responsible for decision-making in manufacturing firms.

Study Area

The study was conducted in Delta State, Nigeria, a key industrial hub in the South-South region of the country. Delta State hosts a variety of manufacturing firms, including agro-processing, food and beverage, chemical, and light engineering companies. These firms were selected due to their active adoption of information and communication technologies, including artificial intelligence tools, in operational and managerial processes (Obi & Okwu, 2020).

Study Population

The study population comprised managerial and supervisory staff in selected manufacturing firms in Delta State. A total of 42 manufacturing firms were purposively selected based on their operational size and technological adoption levels. The population included managers responsible for production, operations, quality control, and supply chain management. The estimated study population consisted of 560 managers and supervisors across the selected firms.

Sample Population

The sample size for this study was determined using Taro Yamane's formula at a 95% confidence level and a 5% margin of error. As shown in Table 1, a total of 234 respondents was proportionately drawn from the population of 560 managers and supervisors across different manufacturing firm categories, ensuring adequate representation of each group. (Yamane, 1967).

Sampling Techniques

The study employed a purposive sampling technique to select manufacturing firms with a demonstrated use of AI in operations. Within these firms, a simple random sampling technique was used to select managerial and supervisory respondents to ensure representativeness and minimize selection bias (Etikan, Musa, & Alkassim, 2016).

Sources of Data Collection

Data were obtained from primary sources, primarily through structured questionnaires administered to managers and supervisors. This method allows for direct measurement of respondents' experiences with AI tools and their influence on managerial decision-making (Creswell & Creswell, 2018).

Method of Data Collection

Questionnaires were distributed in person and via email to respondents in the selected manufacturing firms. A total of 260 questionnaires were distributed, out of which 248 were returned, and 234 were valid for analysis after screening for completeness and consistency.

Instruments of Data Collection

A structured questionnaire was developed based on a five-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree). The questionnaire measured: Independent variables: AI sub-variables including descriptive analytics, diagnostic analytics, machine learning, and robotic process automation. Dependent variable: Managerial decision-making, measured by decision quality, speed, accuracy, and evidence-based decision adoption.

Validity of Instruments

The questionnaire was reviewed by three experts in management and AI to ensure content and construct validity. A pilot study was conducted with 20 managers outside the main sample to refine ambiguous items. The Content Validity Index (CVI) was above 0.80, indicating adequate validity (Polit & Beck, 2006).

Reliability of Instruments

The reliability of the research instrument was evaluated using Cronbach's alpha to determine the internal consistency of the items measuring each construct. As

Table 2: Cronbach's Alpha Reliability Results for Study Variables

Variable	No. of Items	Cronbach's Alpha
Descriptive Analytics	5	0.82
Diagnostic Analytics	5	0.85
Managerial Decision-Making	6	0.88

Table 3: Questionnaire Distribution and Response Rate

Description	Frequency
Questionnaires Distributed	260
Questionnaires Returned	248
Invalid Questionnaires	14
Valid Questionnaires	234
Response Rate (%)	90%

Table 4: Demographic Profile

Variable	Category	Frequency	Percentage (%)
Gender	Male	140	59.8
	Female	94	40.2
Age	20–29	52	22.2
	30–39	110	47.0
	40–49	50	21.4
	50+	22	9.4
Education	Diploma	30	12.8
	Bachelor's Degree	150	64.1
	Master's Degree	44	18.8
	Doctorate	10	4.3
Experience	1–5 years	60	25.6
	6–10 years	102	43.6
	11–15 years	50	21.4
	16+ years	22	9.4

shown in Table 2, all variables demonstrated strong reliability, with alpha values exceeding the recommended threshold of 0.70, indicating that the instrument is suitable for further analysis. (Nunnally & Bernstein, 1994)

Method of Data Analysis

Data were analyzed using descriptive and inferential statistics. Descriptive Statistics: Frequencies, percentages, means, and standard deviations were used to summarize respondent demographics and the extent of AI adoption. Correlation Analysis: Pearson correlation was employed to examine relationships between AI sub-variables and managerial decision-making. Regression Analysis: Multiple regression analysis was conducted to determine the effect of descriptive analytics and diagnostic analytics on managerial decision-making, controlling for firm size and technological infrastructure.

Model Specification:

The relationship between AI and managerial decision-making was specified as:

$$MDM = \beta_0 + \beta_1 DA + \beta_2 DIA + \epsilon$$

Where:

- MDM = Managerial Decision-Making (dependent variable)
- DA = Descriptive Analytics (independent variable)
- DIA = Diagnostic Analytics (independent variable)
- β_0 = Intercept, β_1, β_2 = Regression coefficients, ε = Error term

This model allows the study to quantify the effect of AI tools on decision quality, speed, and accuracy in manufacturing firms in Delta State.

RESULTS AND DISCUSSIONS

Demographic Analyses of Respondents

A total of 260 questionnaires were distributed to respondents across selected manufacturing firms in Delta State. Out of these, 248 were returned, while 14 were invalidated, resulting in 234 valid responses used for analysis. This represents a 90% effective response rate, which is adequate for statistical analysis Table 3. (Baruch & Holtom, 2008).

Demographic Characteristics of Respondents

The results of Table 4 indicate that most respondents were male (59.8%), aged 30–39 years (47%), with a bachelor's

Table 5: Scale Reliability (Cronbach's Alpha)

Variable	Items	Cronbach's Alpha
Machine Learning	5	0.84
Robotic Process Automation (RPA)	5	0.81
Managerial Decision-Making	6	0.87

Table 6: Descriptive Statistics

Variable	Mean	Std. Dev.	Interpretation
Machine Learning	4.08	0.60	High adoption
Robotic Process Automation (RPA)	3.92	0.65	Moderate–High
Managerial Decision-Making	4.10	0.57	High effectiveness

Table 7: Pearson Correlation Matrix

Variables	1	2	3
Machine Learning	1		
RPA	0.58**	1	
Managerial Decision-Making	0.66**	0.61**	1

Note: $p < 0.01$

Table 8: Regression Results

Predictor	B	Std. Error	Beta	t	Sig.
Machine Learning	0.435	0.070	0.462	6.21	0.000
RPA	0.372	0.068	0.401	5.47	0.000
Constant	1.102	0.240	-	4.59	0.000

Model Summary:
$R^2 = 0.60$
Adjusted $R^2 = 0.59$
$F(2, 231) = 173.2, p < 0.001$

Both predictors significantly influence managerial decision-making.

degree (64.1%), and had 6–10 years of experience (43.6%), suggesting adequate experience with AI tools and decision-making processes.

Preliminary Analysis: Data Screening, Missingness & Reliability

Data screening revealed minimal missing values (<2%), which were handled using mean substitution (Hair et al., 2019). No significant outliers were detected. The dataset was deemed suitable for further analysis.

Reliability (Internal Consistency)

The internal consistency of the measurement scales was assessed using Cronbach's alpha. As presented in Table 5, all constructs recorded alpha values above the recommended threshold of 0.70, indicating that the items used to measure each variable are reliable and suitable for further statistical analysis. (Nunnally & Bernstein, 1994).

Descriptive Statistics (Scale Level)

The descriptive statistics of the study variables were computed to examine the central tendency and variability of responses. As shown in Table 6, the mean scores indicate relatively high levels of adoption of AI tools and effectiveness in managerial decision-making, with moderate variability across responses.

Correlation Analysis

The Pearson correlation analysis was conducted to examine the relationships among the study variables. As presented in Table 7, there are strong positive and statistically significant relationships between the AI variables and managerial decision-making, indicating that increases in AI adoption are associated with improved decision outcomes. (Brynjolfsson & McElheran, 2019).

Regression Analysis

Multiple regression analysis was performed to assess the influence of AI variables on managerial decision-making. As shown in Table 8, both machine learning and robotic process automation have significant positive effects on managerial decision-making, indicating their strong predictive power in the model.

DISCUSSION

Effect of Machine Learning on Managerial Decision-Making

The findings revealed that machine learning has a significant positive effect on managerial decision-making in manufacturing firms in Delta State (β = 0.462, $p < 0.001$). This suggests that machine learning enhances decision quality by enabling managers to analyze complex datasets, predict trends, and optimize operational processes. The result supports prior studies that emphasize the role of machine learning in improving forecasting accuracy and decision efficiency (Davenport & Ronanki, 2018; Russell & Norvig, 2021). Manufacturing firms leveraging machine learning can reduce uncertainty and make more informed strategic decisions.

Effect of Robotic Process Automation (RPA) on Managerial Decision-Making

The study also found that RPA significantly influences managerial decision-making (β = 0.401, $p < 0.001$). RPA improves decision-making by automating repetitive tasks, ensuring data accuracy, and providing real-time operational insights. This allows managers to focus on strategic issues rather than routine processes. The finding aligns with existing research indicating that RPA enhances efficiency and supports evidence-based managerial decisions (Aguirre & Rodriguez, 2017; Lacity & Willcocks, 2016). Overall, the results confirm that artificial intelligence tools—specifically machine learning and RPA—are critical drivers of managerial decision-making effectiveness. Firms that adopt these technologies are better positioned to improve decision speed, accuracy, and strategic responsiveness in a competitive manufacturing environment.

Conclusion

The study concludes that artificial intelligence tools, particularly machine learning and robotic process automation (RPA), have a significant positive effect on managerial decision-making in manufacturing firms in Delta State. Machine learning enhances decision quality by enabling managers to analyze complex data, predict trends, and reduce uncertainty, while RPA improves decision efficiency through automation, accuracy, and real-time insights. Overall, the integration of these AI technologies strengthens decision speed, accuracy, and strategic responsiveness, thereby improving managerial effectiveness in a competitive manufacturing environment.

Recommendations

i. Manufacturing firms in Delta State should invest in machine learning systems and training to enhance data analysis capabilities, improve forecasting accuracy, and support informed strategic decision-making.
ii. Firms should deploy RPA to automate routine operational tasks and improve data accuracy, thereby enabling managers to focus on high-level strategic decisions and improve overall decision-making efficiency.

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