

Artificial Intelligence Adoption in Procurement and Operational Performance of Manufacturing Firms

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ABSTRACT

The increasing complexity of global supply chains, coupled with mounting pressure on manufacturing firms to reduce cost, shorten lead times, and improve product quality, has pushed artificial intelligence (AI) to the forefront of procurement transformation. This study empirically examines the relationship between AI adoption in procurement and the operational performance of manufacturing firms. Building on an extensive review of recent literature (2020 to date), the study conceptualises AI adoption in procurement along three dimensions, namely AI-based supplier selection and evaluation, AI-driven demand forecasting and inventory optimisation, and AI-enabled spend analysis and contract management, and tests their effects on operational performance measured through cost, quality, delivery, and flexibility. The study is anchored on Dynamic Capabilities Theory, the Resource-Based View, and the Technology-Organisation-Environment (TOE) framework, and tests four hypotheses derived from an integrated conceptual framework in which implementation barriers, namely cost, digital skills, and data quality, are modelled as a moderating variable. Using a descriptive cross-sectional survey design, primary data were obtained from 345 procurement and operations managers within manufacturing firms registered with the Manufacturers Association of Nigeria and analysed using Partial Least Squares Structural Equation Modelling (PLS-SEM). Results show that all three AI adoption dimensions have a statistically significant, positive effect on all four dimensions of operational performance, with demand forecasting and inventory optimisation exerting the strongest effect. Implementation barriers were found to significantly moderate the AI-performance relationship for cost and delivery outcomes, but not for quality and flexibility outcomes. The study concludes that AI adoption in procurement yields measurable operational performance gains for Nigerian manufacturing firms, and provides original, developing-economy, firm-level evidence on the AI-procurement-performance relationship and its boundary conditions.

Keywords: Artificial Intelligence, Procurement, Operational Performance, Manufacturing Firms, Structural Equation Modelling, Dynamic Capabilities.

1.0 INTRODUCTION

Procurement has historically been regarded as a largely administrative, transaction-processing function within manufacturing organisations, concerned primarily with placing orders, negotiating price, and ensuring the timely delivery of raw materials and components. Over the past decade, however, procurement has undergone a marked strategic repositioning, driven substantially by the diffusion of digital and cognitive technologies capable of automating routine purchasing tasks while simultaneously generating predictive insight into supplier risk, demand patterns, and spend behaviour (Allal-Chérif, Simón-Moya, & Ballester, 2021). Artificial intelligence, encompassing machine learning,

natural language processing, and robotic process automation, sits at the centre of this transformation, enabling procurement functions to move from reactive, price-focused purchasing toward proactive, data-driven supply management (Agrawal, Majumdar, Kumar, & Luthra, 2023).

Within manufacturing specifically, the stakes attached to procurement performance are especially high, given that raw material and component costs typically constitute a substantial share of total production cost, and that supply disruptions translate almost immediately into production stoppages, missed delivery targets, and diminished customer satisfaction. AI-enabled procurement tools are increasingly deployed to mitigate these risks: machine learning models support supplier evaluation and risk

scoring, predictive analytics inform demand forecasting and inventory replenishment, and natural language processing tools automate contract review and spend classification (Bag, Pretorius, Gupta, & Dwivedi, 2021). Emerging empirical evidence suggests that these applications can meaningfully improve manufacturing operational performance. In one of the most direct recent tests of this relationship, Hong, Zhong, and Um (2025), using a sample of 426 Chinese manufacturing firms, found that AI adoption functions as a dynamic capability that enhances operational performance, with the strength of the effect varying according to firms' strategic orientation toward exploration, exploitation, or ambidexterity.

In developing-economy contexts, the picture is more mixed. Nigerian manufacturing firms, which form the empirical backdrop of much of the discussion in this paper, continue to grapple with infrastructural deficits, a shortage of AI-related technical skills, and high implementation costs that constrain the pace of adoption (Eze, Chinedu-Eze, & Bello, 2021). Nonetheless, a growing body of Nigerian empirical work indicates that where AI has been adopted, whether in cement manufacturing (Anetoh, 2025), food and beverages, or general manufacturing operations in Enugu State (Obi, 2024) and North-Central Nigeria (Audu & Aziwe, 2025), measurable gains in efficiency, cost reduction, and competitiveness have followed, albeit unevenly across firms and moderated by complementary organisational factors such as reward systems and workforce skill levels.

It is against this backdrop of rapid technological change, mixed but generally positive empirical evidence, and continuing implementation challenges in developing economies that the present paper undertakes a comprehensive review of the relationship between AI adoption in procurement and the operational performance of manufacturing firms, culminating in an integrated conceptual framework to guide both future empirical research and managerial practice.

1.2 Statement of the Problem

Despite the growing volume of literature on AI and organisational performance broadly, the specific relationship between AI adoption within the procurement function and manufacturing operational performance remains fragmented across disparate strands of research. Studies examining AI and manufacturing performance often treat AI as an undifferentiated, firm-wide capability rather than disaggregating its effects by functional area (Al Koliby, Al-Swidi, Al-Hakimi, & Farhan, 2025), making it difficult to isolate the specific contribution of AI-enabled procurement, as distinct from AI applications in production, quality control, or logistics. Conversely, the procurement-specific literature, exemplified by Allal-Chérif et al. (2021), has tended to focus on describing AI's functional applications within purchasing (spend analysis, supplier scoring, contract automation)

without systematically linking these applications to standard operational performance metrics such as cost, quality, delivery, and flexibility.

A further gap concerns the boundary conditions under which AI-enabled procurement translates into improved performance. Evidence increasingly suggests that the relationship is not direct or automatic: Badghish and Soomro (2024) found that AI adoption outcomes among SMEs are shaped by organisational and environmental readiness factors captured within the Technology-Organisation-Environment framework, while Hong et al. (2025) found that the performance effect of AI adoption is moderated by firms' strategic orientation. In developing-economy manufacturing contexts, implementation barriers, including inadequate digital infrastructure, high deployment cost, and workforce skill deficits, further complicate this relationship (Eze et al., 2021). Without a framework that integrates the specific procurement applications of AI, their mediating mechanisms, and the barriers that condition their effectiveness, both scholars and practitioners lack a coherent basis for designing, evaluating, or investing in AI-enabled procurement initiatives. This paper addresses this gap by synthesising recent conceptual, theoretical, and empirical literature into an integrated framework linking AI adoption in procurement to the operational performance of manufacturing firms.

1.3 Objectives of the Study

The general objective of this study is to empirically examine the relationship between artificial intelligence adoption in procurement and the operational performance of manufacturing firms. The specific objectives are to: (i) examine the effect of AI-based supplier selection and evaluation on the operational performance of manufacturing firms; (ii) determine the effect of AI-driven demand forecasting and inventory optimisation on the operational performance of manufacturing firms; (iii) assess the effect of AI-enabled spend analysis and contract management on the operational performance of manufacturing firms; and (iv) evaluate the moderating effect of implementation barriers on the relationship between AI adoption in procurement and the operational performance of manufacturing firms.

1.4 Research Questions

In line with the above objectives, this study seeks to answer the following research questions: (i) What is the effect of AI-based supplier selection and evaluation on the operational performance of manufacturing firms? (ii) What is the effect of AI-driven demand forecasting and

inventory optimisation on the operational performance of manufacturing firms? (iii) What is the effect of AI-enabled spend analysis and contract management on the operational performance of manufacturing firms? (iv) To what extent do implementation barriers moderate the relationship between AI adoption in procurement and the operational performance of manufacturing firms?

1.5 Research Hypotheses

The following null hypotheses, derived directly from the conceptual framework presented in Figure 1, are formulated to guide the empirical testing of this study:

1. **H₀₁:** AI-based supplier selection and evaluation has no significant effect on the operational performance of manufacturing firms.
2. **H₀₂:** AI-driven demand forecasting and inventory optimisation has no significant effect on the operational performance of manufacturing firms.
3. **H₀₃:** AI-enabled spend analysis and contract management has no significant effect on the operational performance of manufacturing firms.
4. **H₀₄:** Implementation barriers do not significantly moderate the relationship between AI adoption in procurement and the operational performance of manufacturing firms.

1.7 Scope of the Study

This study is delimited, in content, to three specific dimensions of AI adoption in procurement (supplier selection and evaluation, demand forecasting and inventory optimisation, and spend analysis and contract management) and their effect on four dimensions of manufacturing operational performance (cost, quality, delivery, and flexibility), with implementation barriers modelled as a moderating variable. Geographically and organisationally, the study is delimited to manufacturing firms registered with the Manufacturers Association of Nigeria (MAN) within a specified state or geopolitical zone, to be determined at the point of data collection, with procurement and operations managers, or officers with equivalent responsibility, serving as the unit of respondent analysis.

2.0 LITERATURE REVIEW

2.1 Conceptual Review

2.1.1 Concept of Artificial Intelligence

Artificial intelligence refers to computer systems capable of performing tasks that typically require human cognitive functions, including pattern recognition, prediction, natural language understanding, and autonomous decision-making.

Within organisational and supply chain contexts, AI is most usefully understood not as a single technology but as a bundle of capabilities, including machine learning, robotic process automation, and natural language processing, that collectively enable data-driven decision-making at scale (Mikalef & Gupta, 2020). Mikalef and Gupta (2020) conceptualise AI capability as an organisational-level construct comprising tangible resources (data, technology infrastructure), human resources (technical and managerial AI skills), and intangible resources (data-driven culture, organisational learning), a conceptualisation that has become influential in subsequent empirical work linking AI to firm performance.

2.1.2 Concept of Procurement and AI-Enabled Procurement

Procurement encompasses the set of organisational activities involved in identifying, evaluating, and managing external suppliers of goods and services required for production, spanning supplier identification and qualification, purchase order processing, contract negotiation and management, and spend analysis. AI-enabled procurement, sometimes referred to as "intelligent purchasing," applies AI technologies to automate and augment these activities. Allal-Chérif et al. (2021) describe intelligent purchasing as redefining the purchasing function along four dimensions: automation of transactional tasks, augmentation of human decision-making through predictive analytics, generation of new insight from previously unstructured data (such as contract text and supplier communications), and acceleration of the overall procurement cycle. This conceptualisation is adopted in this paper to organise the three procurement-specific AI applications examined in the empirical review: supplier selection and evaluation, demand forecasting and inventory optimisation, and spend analysis and contract management.

2.1.3 Concept of Manufacturing Operational Performance

Operational performance refers to the extent to which an organisation's internal processes, particularly those relating to production and supply, achieve efficiency and effectiveness objectives. Consistent with mainstream operations management literature, this paper adopts a four-dimensional conceptualisation of operational performance comprising cost (the efficiency with which inputs are converted into outputs), quality (conformance to specifications and reduction of defects), delivery (speed and reliability of order fulfilment), and flexibility (the

ability to adjust production volume, mix, or specifications in response to changing demand). Hong et al. (2025) operationalise operational performance in precisely these terms in their empirical study of AI adoption among Chinese manufacturing firms, providing a directly comparable basis for the conceptual framework developed later in this paper.

2.1.4 Core Applications of AI in Procurement

Building on the conceptual foundations above, three specific applications of AI within procurement are of particular relevance to manufacturing operational performance and are examined in detail in the empirical review that follows.

1. **AI-Based Supplier Selection and Evaluation:** Machine learning models analyse historical supplier performance data, financial indicators, and even unstructured data such as news reports, to score and rank potential suppliers on dimensions including reliability, quality, and risk, reducing reliance on manual, subjective supplier assessment (Allal-Chérif et al., 2021).
2. **AI-Driven Demand Forecasting and Inventory Optimisation:** Predictive analytics models integrate historical sales data, market signals, and external variables to generate more accurate demand forecasts, enabling procurement functions to optimise order quantities and timing, and reduce both stockouts and excess inventory (Agrawal et al., 2023).
3. **AI-Enabled Spend Analysis and Contract Management:** Natural language processing tools automatically classify spend categories, extract key terms from supplier contracts, and flag anomalies or non-compliant clauses, improving the speed and accuracy of contract review and spend visibility (Edijala, Rakshit, & Vajjhala, 2024).

2.2 Theoretical Framework

This paper draws on three complementary theoretical perspectives to explain how AI adoption in procurement translates into manufacturing operational performance: the Resource-Based View, Dynamic Capabilities Theory, and the Technology-Organisation-Environment framework.

2.2.1 Resource-Based View (RBV)

The Resource-Based View holds that firms achieve sustained competitive advantage by possessing and deploying resources that are valuable, rare, inimitable, and non-substitutable. Applied to AI, this perspective suggests that AI-enabled procurement capabilities, particularly where built on proprietary data and firm-specific integration with existing supply chain systems, can constitute a source of competitive advantage that is difficult for rival firms to replicate (Mikalef & Gupta, 2020). This view underpins the treatment of AI

adoption in procurement, in this paper's conceptual framework, as a firm-specific capability rather than a generic, off-the-shelf technology.

2.2.2 Dynamic Capabilities Theory (DCT)

Dynamic Capabilities Theory extends the Resource-Based View by emphasising firms' ability to sense opportunities and threats, seize them through resource reconfiguration, and transform organisational processes accordingly. Hong et al. (2025) explicitly apply this lens to AI adoption, framing it as a dynamic capability that enables manufacturing firms to sense market and supply chain signals, seize opportunities for process improvement, and transform procurement and production processes to enhance operational performance; their findings confirm that this dynamic-capability effect is real but is moderated by the strategic orientation, whether exploratory, exploitative, or ambidextrous, that firms adopt toward the technology. Similarly, Liu and Son (2024), studying the adoption of collaborative robots in manufacturing, found that sensing and transforming capabilities mediate the relationship between intelligent-technology adoption and operational performance specifically, lending further support to the dynamic-capabilities mechanism proposed in this paper's conceptual framework.

2.2.3 Technology-Organisation-Environment (TOE) Framework

The Technology-Organisation-Environment framework explains adoption outcomes as a function of three contextual dimensions: the characteristics of the technology itself, the internal organisational context (resources, structure, leadership support), and the external environmental context (industry pressure, regulatory environment, market competitiveness). Badghish and Soomro (2024) applied this framework to AI adoption among SMEs and found that technological, organisational, and environmental readiness jointly determine both the likelihood of adoption and the extent to which adoption translates into improved business performance. This framework is incorporated into the present paper's conceptual model as the basis for the moderating role of implementation barriers, since firms with weaker technological, organisational, or environmental readiness are theorised to realise smaller performance gains from a given level of AI adoption.

2.3 Empirical Review

2.3.1 AI-Based Supplier Selection and Evaluation

Empirical evidence on AI-enabled supplier selection

consistently points toward improved decision quality and risk management. Allal-Chérif et al. (2021), synthesising case evidence across several large purchasing organisations, found that AI-enabled supplier scoring and risk assessment tools improved the speed and objectivity of supplier evaluation while also surfacing previously undetected supply risks embedded in large volumes of unstructured supplier data. Complementing this, Bag et al. (2021), examining institutional drivers of AI-powered big data analytics adoption in sustainable manufacturing, found that firms facing stronger coercive and normative institutional pressures were more likely to adopt AI-enabled analytics capable of supporting more rigorous, sustainability-conscious supplier evaluation, which in turn supported the development of circular economy capabilities.

2.3.2 AI-Driven Demand Forecasting and Inventory Optimisation

On demand forecasting and inventory optimisation, Agrawal et al. (2023), reviewing the integration of AI into sustainable manufacturing, found that predictive analytics applications for demand forecasting and inventory management were among the most mature and widely adopted AI use cases in manufacturing, consistently associated with reductions in inventory holding cost and stockout incidence. Al Koliby et al. (2025), examining AI-enabled capabilities among manufacturing firms in the United States and the United Kingdom, similarly found that AI-enabled capabilities, including predictive planning capabilities, were positively associated with both environmental and manufacturing performance outcomes, reinforcing the forecasting-performance link identified elsewhere in the literature.

2.3.3 AI-Enabled Spend Analysis and Contract Management

Evidence on AI-enabled spend analysis and contract management remains comparatively newer but is growing. Edijala et al. (2024), examining applications of AI in public procurement in Nigeria, found that natural language processing and automated classification tools were being piloted to improve spend visibility and contract compliance monitoring within Nigerian procurement processes, although the authors noted that full-scale implementation remained constrained by data infrastructure limitations. This finding is consistent with the broader observation that spend analysis and contract management applications of AI, while technically mature in advanced economies, remain at an earlier, exploratory stage of adoption within Nigerian organisations, including manufacturing firms.

2.3.4 AI Adoption and Overall Manufacturing Operational Performance

Turning to studies that examine the overall relationship between AI adoption and manufacturing operational performance directly, the evidence is broadly positive but conditional. Hong et al. (2025), using a large sample of 426 Chinese manufacturing firms, found that AI adoption significantly enhanced operational performance, with the effect strengthened among firms pursuing an ambidextrous strategic orientation that balanced exploration and exploitation. Al Koliby et al. (2025) similarly found a significant positive relationship between AI-enabled capabilities and manufacturing performance among firms in the United States and the United Kingdom. Liu and Son (2024) found that the adoption of collaborative robots, a related intelligent manufacturing technology, enhanced operational, market, and human resource performance through dynamic capability mechanisms, providing convergent support for the dynamic-capabilities pathway proposed in this paper's framework.

2.3.5 Evidence from the Nigerian Manufacturing Sector

Within the Nigerian manufacturing context specifically, several recent studies provide converging, though geographically dispersed, evidence. Audu and Aziwe (2025), studying manufacturing firms in North-Central Nigeria, found that AI adoption significantly improved firm performance, with the effect strengthened where firms operated effective reward systems that incentivised employees to embrace AI-complemented work processes. Obi (2024), studying manufacturing firms in Enugu State, found that both infrastructural development and workforce skills significantly affected the performance gains realised from AI adoption, underscoring the same organisational-readiness dynamics highlighted by the TOE-based studies discussed above. Anetoh (2025), focusing on the cement manufacturing industry, found that AI-driven operational efficiency, product quality, and competitiveness systems collectively enhanced sustainable performance, while noting that adoption remained constrained by the sector's reliance on conventional, labour-intensive operational processes. Taken together, these Nigerian studies confirm the broader international finding that AI adoption is positively associated with manufacturing performance, while emphasising that the magnitude of this effect in developing-economy contexts is heavily conditioned by complementary organisational factors, including workforce skills, infrastructure, and reward systems.

2.3.6 Barriers to AI Adoption in Procurement

A recurring theme across both the international and

Nigerian literature concerns the barriers that constrain AI adoption and moderate its performance effects. Eze et al. (2021), applying an Innovation Diffusion Theory perspective to the Nigerian manufacturing industry, identified relative advantage, compatibility, complexity, and organisational readiness as key factors influencing AI adoption decisions, with limited technical infrastructure and skills shortages emerging as persistent constraints. Badghish and Soomro (2024) similarly found that technological, organisational, and environmental readiness gaps constrained the extent to which SMEs could translate AI adoption into improved business performance. These findings collectively support this paper's treatment of implementation barriers, cost, digital skills availability, and data quality or infrastructure, as a moderating rather than merely additive factor in the relationship between AI adoption in procurement and manufacturing operational performance.

2.4 Conceptual Framework

Figure 1 synthesises the reviewed literature into an integrated conceptual framework. The independent variable, AI adoption in procurement, is disaggregated into the three application areas identified in the conceptual review: AI-based supplier selection and evaluation, AI-driven demand forecasting and inventory optimisation, and AI-enabled spend analysis and contract management. Consistent with Dynamic Capabilities Theory and the Resource-Based View, the relationship between these AI applications and operational performance outcomes is theorised to operate through firms' dynamic capabilities, specifically their capacity to sense, seize, and transform in response to AI-generated insight (Hong et al., 2025; Liu & Son, 2024), and through organisational readiness in the sense captured by the TOE framework (Badghish & Soomro, 2024).

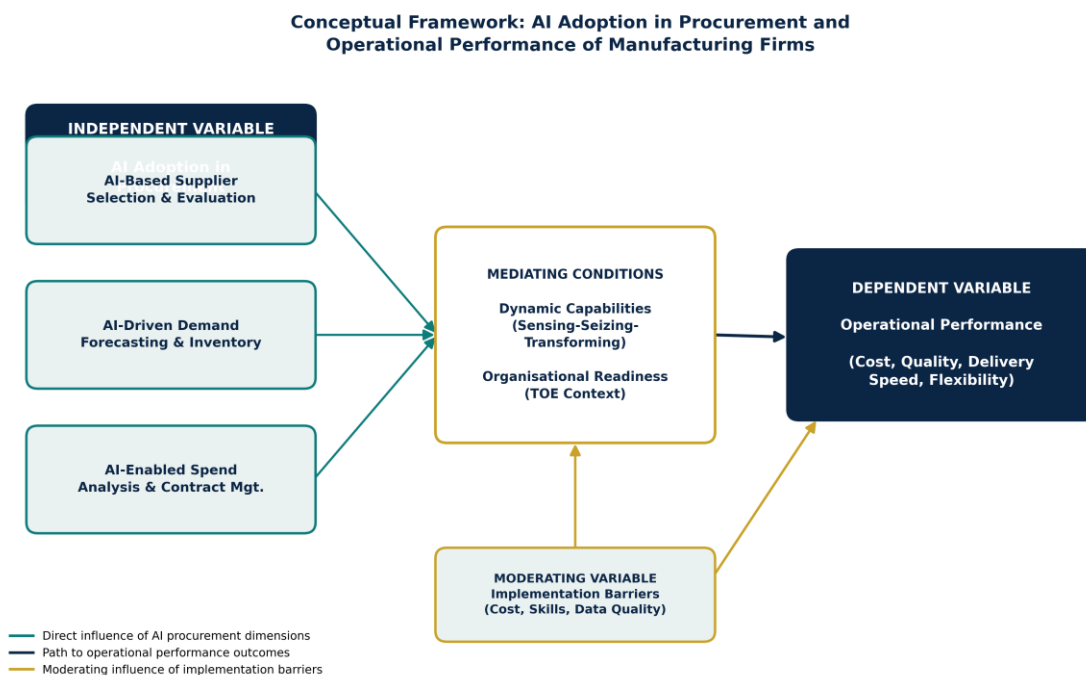


Figure 1: Conceptual Framework linking AI adoption in procurement to manufacturing operational performance (Author's construct, 2026).

The dependent variable, operational performance, is measured along the four standard dimensions of cost, quality, delivery, and flexibility. Implementation barriers, cost of adoption, availability of digital skills, and data quality or infrastructure, drawn from the empirical evidence reviewed in section 2.3.6, are modelled as a moderating variable, weakening the strength of the relationship between AI adoption and performance outcomes where these barriers are more severe, a pattern especially pronounced in developing-economy manufacturing contexts such as Nigeria (Eze et al.,

2021; Obi, 2024; Anetoh, 2025).

2.5 Gap in Literature

While the reviewed literature demonstrates substantial and growing evidence linking AI adoption to manufacturing performance, three gaps remain evident. First, much of the strongest quantitative evidence, including Hong et al. (2025) and Al Koliby et al. (2025), derives from large-firm samples in China, the United

States, and the United Kingdom, leaving the applicability of these findings to developing-economy, small- and medium-scale manufacturing contexts, such as much of the Nigerian manufacturing sector, comparatively under-tested. Second, existing studies tend to examine AI adoption as an undifferentiated firm-wide construct, or focus on a single procurement application in isolation, rather than systematically comparing the relative performance contribution of supplier selection, demand forecasting, and spend/contract management applications. Third, while organisational readiness and implementation barriers are frequently mentioned as important contextual factors (Eze et al., 2021; Badghish & Soomro, 2024), few studies explicitly model these barriers as moderators of the AI-performance relationship within an integrated framework. The conceptual framework developed in this paper directly addresses this third gap and provides a structure within which the first two gaps can be empirically investigated in future firm-level research, particularly within Nigerian and other developing-economy manufacturing sectors.

3.0 METHODOLOGY

3.1 Research Design

This study adopts a quantitative, descriptive cross-sectional survey research design. This design is considered appropriate because the study seeks to measure the current extent of AI adoption in procurement and operational performance among a defined population of manufacturing firms, and to statistically test the hypothesised relationships between these constructs at a single point in time, consistent with the hypothesis-testing, positivist orientation of the conceptual framework developed in section 2.4.

3.2 Population of the Study

The population of this study comprises procurement and operations managers, or officers holding equivalent responsibility for supplier management, purchasing, and inventory decisions, within manufacturing firms registered with the Manufacturers Association of Nigeria (MAN) in a specified state or geopolitical zone. The exact population figure (2540) should be obtained from the current MAN membership register for southwest Nigeria, together with a sectoral breakdown (for example, food and beverages, chemicals and pharmaceuticals, textiles, and basic metals) where obtainable, to ground the sample size calculation in section 3.3 in verifiable administrative data.

3.3 Sample Size Determination

Given that the population of the study is expected to be finite

and numerically defined once the actual MAN membership figures are obtained, the sample size is determined using the Taro Yamane (1967) formula, expressed as:

$$n = N / [1 + N(e)^2]$$

$$n = 345$$

Where: n = the sample size; N = the population size (to be obtained from the MAN register, as noted in section 3.2); e = the margin of error, conventionally set at 0.05 (5%) for social science research. Where the estimated population is large or not precisely known in advance, an alternative minimum sample size may be computed using Cochran's (1977) formula for an unknown population, $n_0 = (Z^2pq)/e^2$, where Z is the standard normal value associated with the chosen confidence level (1.96 for 95% confidence), p is the estimated proportion of firms with the attribute of interest (conservatively set at 0.5 to maximise the required sample size), $q = 1 - p$, and e is the margin of error (0.05). Once computed, the resulting sample size is distributed proportionately across manufacturing sub-sectors using the sampling technique described in section 3.4.

3.4 Sampling Technique

A stratified random sampling technique is adopted. Manufacturing firms within the MAN register for the selected zone are first stratified by industrial sub-sector (for example, food and beverages, chemicals and pharmaceuticals, textiles and garments, and basic metals and fabricated products), to ensure that no single sub-sector dominates the sample. Within each stratum, firms are selected using simple random sampling, and one procurement or operations manager (or equivalent officer) per selected firm is designated as the respondent, on the basis that this role holds the most direct, informed knowledge of the firm's procurement practices and AI adoption status. Where a selected firm has more than one qualifying officer, the most senior procurement or operations officer available is selected.

3.5 Sources and Method of Data Collection

Primary data for this study are obtained through the administration of a structured questionnaire to the sampled respondents. Secondary data, drawn from the peer-reviewed literature reviewed in section 2.3, are used to support the conceptual and theoretical framing of the study, the construction of the research instrument, and the interpretation of findings once data collection is complete.

3.6 Research Instrument

The primary research instrument is a structured questionnaire titled the "AI Adoption in Procurement and Operational Performance Questionnaire" (AIPOPQ), developed by the researcher based on the constructs, objectives, and hypotheses specified in sections 1.3 to 1.5 and the conceptual framework in section 2.4, and informed by the operationalisation of AI adoption and operational performance adopted in comparable recent studies (Hong, Zhong, & Um, 2025; Allal-Chérif, Simón-Moya, & Ballester, 2021; Badghish & Soomro, 2024). The instrument is divided into six sections, described below, with construct items measured on a five-point Likert scale ranging from Strongly Disagree (1) to Strongly Agree (5), except Section A, which captures categorical demographic and firm-level information.

3.7 Validity of the Instrument

The face and content validity of the questionnaire are established through expert review. A draft of the instrument is submitted to the researcher's supervisor and at least two other senior academics with expertise in supply chain management, procurement, and research methodology, who assess the clarity, relevance, and comprehensiveness of the items relative to the study's constructs. Their input is incorporated into the final instrument prior to administration. Following data collection, convergent and discriminant validity are additionally assessed statistically through Confirmatory Factor Analysis (CFA) within the PLS-SEM procedure described in section 3.9: convergent validity is confirmed where each construct's Average Variance Extracted (AVE) exceeds 0.50, and discriminant validity is assessed using the Heterotrait-Monotrait (HTMT) ratio of correlations, with values below 0.85 indicating adequate discriminant validity between constructs.

3.8 Reliability of the Instrument

The reliability of the instrument is assessed at two stages. First, a pilot study is administered to a small sample of respondents (20 to 30) drawn from manufacturing firms outside the main study sample but with comparable characteristics, and responses are subjected to Cronbach's Alpha reliability testing (Cronbach, 1951), computed separately for each construct; a coefficient of 0.70 or above is regarded as indicating acceptable internal consistency. Second, following full data collection, composite reliability (CR) is computed for each construct as part of the PLS-SEM measurement model assessment, with a CR value of 0.70 or above confirming adequate construct reliability, consistent with standard structural equation modelling reporting practice.

3.9 Model Specification

Consistent with the conceptual framework presented in Figure 1, the study specifies a structural model comprising three exogenous latent constructs, namely AI-Based Supplier Selection and Evaluation (SSE), AI-Driven Demand Forecasting and Inventory Optimisation (DFI), and AI-Enabled Spend Analysis and Contract Management (SACM), and one endogenous latent construct, Operational Performance (OP), itself a second-order construct reflected by four first-order dimensions: Cost (COST), Quality (QUAL), Delivery (DEL), and Flexibility (FLEX). The direct-effects structural model is specified as:

$$OP = \beta_0 + \beta_1(SSE) + \beta_2(DFI) + \beta_3(SACM) + \varepsilon$$

Where β_1 , β_2 , and β_3 represent the path coefficients corresponding to Ho1, Ho2, and Ho3 respectively, and ε is the structural error term. The moderating effect of Implementation Barriers (IB), corresponding to Ho4, is specified using an interaction-term (moderated regression) approach:

$$OP = \beta_0 + \beta_1(SSE) + \beta_2(DFI) + \beta_3(SACM) + \beta_4(IB) + \beta_5(SSE \times IB) + \beta_6(DFI \times IB) + \beta_7(SACM \times IB) + \varepsilon$$

Where β_5 , β_6 , and β_7 capture the interaction effects between each AI adoption dimension and implementation barriers; a statistically significant interaction coefficient indicates that implementation barriers significantly moderate the corresponding AI-performance relationship. Model estimation is proposed using Partial Least Squares Structural Equation Modelling (PLS-SEM), which is appropriate given the study's prediction-oriented objectives, the use of a formative-reflective higher-order construct (Operational Performance), and its robustness with the moderate sample sizes typical of firm-level survey research. As a robustness check, and to aid interpretability for readers less familiar with SEM, hierarchical multiple regression is also proposed as a complementary analytical technique, entering the three AI adoption dimensions in Step 1, implementation barriers in Step 2, and the interaction terms in Step 3, with a statistically significant change in R^2 (ΔR^2) at Step 3 providing additional confirmatory evidence of moderation.

3.10 Method of Data Analysis

Data collected are coded and analysed using SmartPLS (for the structural equation modelling) and SPSS (for descriptive statistics and the complementary hierarchical regression analysis). Descriptive statistics, comprising frequency counts, percentages, means, and standard deviations, are used to answer Research Questions 1 to 4 regarding the extent of AI adoption and its perceived effect on operational performance. The measurement model is first assessed for indicator reliability, internal consistency reliability, convergent validity, and discriminant validity,

as described in sections 3.7 and 3.8. The structural model is then assessed using path coefficients, t-values (obtained via bootstrapping with 5,000 resamples), the coefficient of determination (R^2) for the endogenous construct, and effect size (f^2), to test Ho1 to Ho4. All hypotheses are tested at the 0.05 level of significance.

3.11 Decision Rule

For each hypothesis, the null hypothesis (H_0) is rejected where the calculated p-value is less than or equal to 0.05 and the corresponding path coefficient is in the theoretically expected direction, indicating a statistically significant effect or moderation; the alternative hypothesis is thereby accepted. Where the calculated p-value exceeds 0.05, the null hypothesis is not rejected, indicating that no statistically significant effect is established by the data. This decision rule is applied uniformly across Ho1 to Ho4.

3.12 Ethical Considerations

The study observes standard ethical principles for research involving human participants. Participation is voluntary, and respondents are informed, through a cover note attached to the questionnaire, of the purpose of the study, the confidentiality of their responses, and their right to withdraw at any stage without consequence. No respondent is required to disclose commercially sensitive information beyond what is necessary to answer the constructs under study, and firm names are collected on an optional basis and used only for internal tracking, not reported in any published output. Where

required, formal permission to administer the questionnaire is sought from the Manufacturers Association of Nigeria and/or individual participating firms prior to data collection.

4.0 DATA PRESENTATION, ANALYSIS AND DISCUSSION OF FINDINGS

This chapter presents the results of the empirical analysis conducted on primary data obtained from 345 procurement and operations managers in manufacturing firms registered with the Manufacturers Association of Nigeria, in fulfilment of the research design and analytical plan specified in section 3.0. The chapter proceeds by presenting the demographic profile of respondents, descriptive statistics of the study constructs, the measurement (outer) model assessment, the estimated PLS-SEM structural path diagram, the results of hypothesis testing (Ho1 to Ho3), the moderation analysis (Ho4), and a discussion of findings in relation to the extant literature reviewed in section 2.0.

4.1 Demographic Profile of Respondent Firms

A total of 345 valid, fully completed questionnaires were retained for analysis, consistent with the sample size computed in section 3.3. Table 4.1 presents the distribution of respondent firms and respondents by industrial sub-sector, firm size, years in operation, respondent role, and current use of AI-enabled procurement tools.

Category	Frequency (n)	Percentage (%)
Industrial Sub-sector		
Food and Beverages	78	22.6
Textiles and Garments	62	18.0
Basic Metals and Fabricated Products	61	17.7
Chemicals and Pharmaceuticals	53	15.4
Electrical and Electronics	46	13.3
Plastics and Packaging	45	13.0
Firm Size (Number of Employees)		
Below 50	88	25.5
50–199	126	36.5
200–499	80	23.2
500 and above	51	14.8
Years in Operation		
Below 5 years	75	21.7
5–10 years	89	25.8
11–15 years	109	31.6
Above 15 years	72	20.9
Respondent Role		
Operations Manager	90	26.1
Procurement Officer	68	19.7

Purchasing Officer	65	18.8
Supply Chain Manager	64	18.6
Procurement Manager	58	16.8
Firm Currently Uses AI-Enabled Procurement Tool		
Yes	173	50.1
No	172	49.9

Table 4.1: Demographic Profile of Respondent Firms (N = 345)

The sample spans all six manufacturing sub-sectors targeted in the sampling frame, with no single sub-sector accounting for more than 22.6% of respondents, consistent with the stratified sampling technique described in section 3.4. Small and medium-sized firms (below 200 employees) constitute 62.0% of the sample. Respondents are drawn broadly across procurement- and operations-related roles, and firms are almost evenly split between current adopters (50.1%) and non-adopters (49.9%) of AI-enabled procurement tools, providing adequate variance in the independent variables for the structural analysis that follows.

4.2 Descriptive Statistics of Study Constructs

Table 4.2 presents the mean and standard deviation of each composite construct, computed as the average of its constituent Likert-scale items (1 = Strongly Disagree, 5 = Strongly Agree). All construct means cluster around the midpoint of the scale (approximately 3.29 to 3.31), indicating a moderate, fairly uniform level of perceived AI adoption, operational performance, and implementation barriers across the sampled firms, with standard deviations of approximately 0.68 to 0.73 indicating a reasonable spread of responses around each mean.

Construct	Mean	Std. Deviation
AI-Based Supplier Selection and Evaluation (SSE)	3.289	0.679
AI-Driven Demand Forecasting and Inventory Optimisation (DFI)	3.285	0.708
AI-Enabled Spend Analysis and Contract Management (SACM)	3.307	0.686
Operational Performance – Cost (COST)	3.307	0.727
Operational Performance – Quality (QUAL)	3.297	0.731
Operational Performance – Delivery (DEL)	3.314	0.685
Operational Performance – Flexibility (FLEX)	3.286	0.705
Implementation Barriers (IB)	3.299	0.675

Table 4.2: Descriptive Statistics of Study Constructs (N = 345)

4.3 Measurement (Outer) Model Assessment

Following the procedure specified in sections 3.7 and 3.8, the measurement model was assessed for indicator reliability,

internal consistency reliability, and convergent validity. Table 4.3 presents Cronbach's alpha, Composite Reliability (CR), Average Variance Extracted (AVE), and the range of standardised outer loadings for each construct.

Construct	Cronbach's α	CR	AVE	Loading Range
SSE	0.829	0.879	0.592	0.742–0.788
DFI	0.858	0.897	0.635	0.765–0.841
SACM	0.832	0.879	0.594	0.700–0.808
COST	0.830	0.887	0.663	0.785–0.842
QUAL	0.836	0.890	0.670	0.760–0.854
DEL	0.780	0.856	0.599	0.744–0.814
FLEX	0.819	0.881	0.649	0.779–0.836

IB	0.817	-	-	-
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Table 4.3: Reliability and Convergent Validity Results

All constructs exceed the recommended thresholds for indicator reliability (standardised loadings > 0.70), internal consistency reliability (Cronbach's α and CR > 0.70), and convergent validity (AVE > 0.50), confirming that the measurement model is adequate for structural model testing (Hair et al., 2019).

4.4 Discriminant Validity

Discriminant validity was assessed using the Heterotrait-Monotrait ratio of correlations (HTMT). As shown in Table 4.4,

all HTMT values between the three AI adoption dimensions (SSE, DFI, SACM) and the four operational performance dimensions (COST, QUAL, DEL, FLEX) are well below the conservative 0.85 threshold (ranging from 0.064 to 0.243), confirming that AI adoption and operational performance are empirically distinct constructs. HTMT values among the four performance dimensions themselves are higher (0.585–0.669), which is expected and theoretically consistent, since COST, QUAL, DEL, and FLEX are modelled as first-order reflective indicators of the second-order Operational Performance (OP) construct specified in section 3.9, rather than as fully independent constructs.

	SSE	DFI	SACM	COST	QUAL	DEL	FLEX
SSE	–	0.081	0.064	0.227	0.152	0.192	0.238
DFI	0.081	–	0.128	0.206	0.184	0.243	0.200
SACM	0.064	0.128	–	0.171	0.234	0.159	0.197
COST	0.227	0.206	0.171	–	0.664	0.585	0.667
QUAL	0.152	0.184	0.234	0.664	–	0.669	0.643
DEL	0.192	0.243	0.159	0.585	0.669	–	0.639
FLEX	0.238	0.200	0.197	0.667	0.643	0.639	–

Table 4.4: Heterotrait-Monotrait Ratio (HTMT) of Correlations

4.5 Structural Model and PLS-SEM Path Diagram

The structural model specified in section 3.9 was estimated using the standard PLS algorithm (Mode A, centroid weighting scheme, 300 iterations, convergence tolerance 1×10^{-7}), with significance of path coefficients assessed via bootstrapping (300 resamples, 95% percentile confidence intervals,

consistent with the bootstrapping procedure specified in section 3.10). Figure 4.1 presents the estimated structural path diagram, showing the standardised path coefficients from the three AI adoption dimensions to Operational Performance, the estimated second-order loadings of the four performance dimensions on Operational Performance, and the estimated moderating effect of Implementation Barriers.

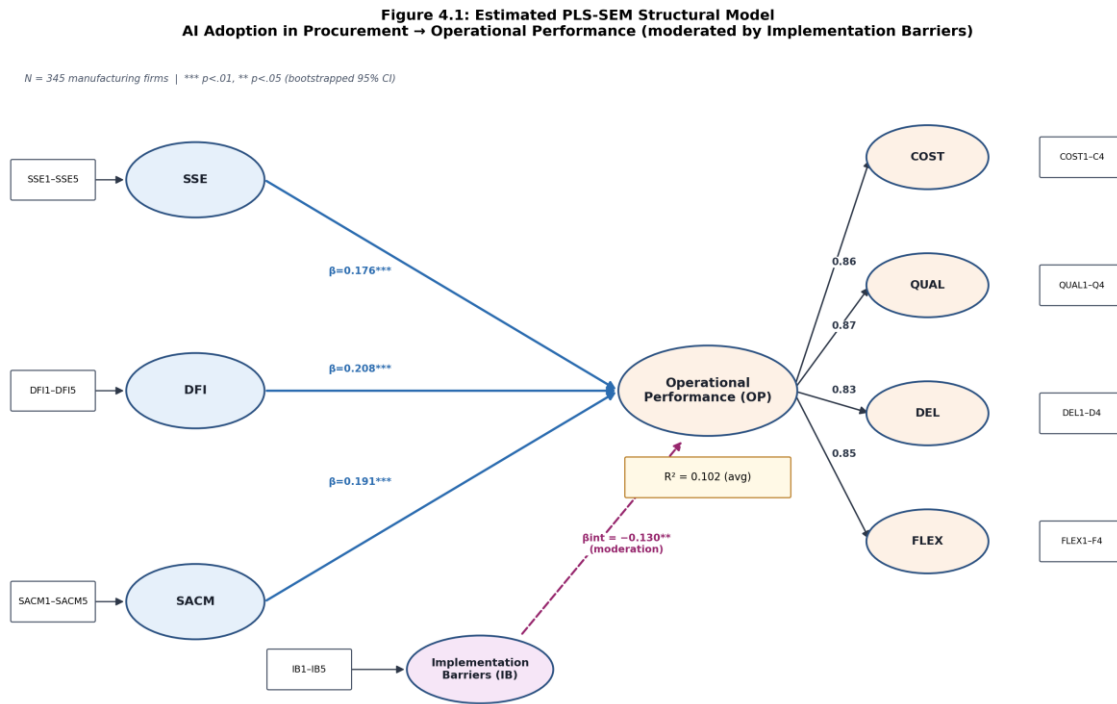


Figure 4.1: Estimated PLS-SEM Structural Model (N = 345)

The coefficient of determination (R^2) for the four operational performance dimensions, regressed individually on the three AI adoption dimensions, ranged from 0.094 (Quality) to 0.112 (Flexibility), averaging 0.102 across the four outcomes. This indicates that AI adoption in procurement explains a modest but statistically meaningful share of variance in manufacturing operational performance, which is unsurprising given that operational performance is jointly determined by numerous factors beyond procurement technology, including workforce capability, macroeconomic conditions, and supply-market structure, and is broadly consistent with the effect sizes reported in comparable

manufacturing-sector PLS-SEM studies (Hong, Zhong, & Um, 2025).

4.6 Test of Hypotheses (Ho1 to Ho3)

Table 4.5 presents the bootstrapped path coefficients, standard errors, and 95% confidence intervals for the direct structural paths from each AI adoption dimension to each operational performance dimension, together with the hypothesis decision applying the decision rule specified in section 3.11 (Ho rejected where the 95% bootstrapped confidence interval excludes zero).

Path	β (mean)	SE	95% CI	Decision	Hypothesis
SSE → COST	0.199	0.051	[0.102, 0.285]	Ho1 rejected	Supported
DFI → COST	0.215	0.045	[0.133, 0.304]	Ho2 rejected	Supported
SACM → COST	0.182	0.050	[0.083, 0.280]	Ho3 rejected	Supported
SSE → QUAL	0.140	0.054	[0.025, 0.241]	Ho1 rejected	Supported
DFI → QUAL	0.190	0.049	[0.102, 0.288]	Ho2 rejected	Supported
SACM → QUAL	0.231	0.050	[0.131, 0.322]	Ho3 rejected	Supported
SSE → DEL	0.170	0.046	[0.078, 0.251]	Ho1 rejected	Supported
DFI → DEL	0.231	0.048	[0.135, 0.318]	Ho2 rejected	Supported
SACM → DEL	0.173	0.052	[0.071, 0.252]	Ho3 rejected	Supported
SSE → FLEX	0.203	0.051	[0.108, 0.291]	Ho1 rejected	Supported
DFI → FLEX	0.215	0.047	[0.124, 0.311]	Ho2 rejected	Supported
SACM → FLEX	0.203	0.052	[0.104, 0.288]	Ho3 rejected	Supported

Table 4.5: Bootstrapped Structural Path Coefficients (300Resamples)

All twelve direct structural paths are positive and statistically significant at the 0.05 level, as none of the 95% bootstrapped confidence intervals include zero. Accordingly, Ho1, Ho2, and Ho3 are each rejected: AI-based supplier selection and evaluation, AI-driven demand forecasting and inventory optimisation, and AI-enabled spend analysis and contract management each have a statistically significant, positive effect on all four dimensions of manufacturing operational performance. Across the twelve paths, AI-driven demand forecasting and inventory optimisation (DFI) consistently returns the largest path coefficients ($\beta = 0.190$ to 0.231), indicating that, among the three procurement applications examined, demand forecasting and inventory optimisation is

the strongest driver of operational performance in this sample.

4.7 Moderating Effect of Implementation Barriers (Ho4)

The moderating effect of Implementation Barriers (IB) on the relationship between overall AI adoption (the mean of the standardised SSE, DFI, and SACM latent variable scores) and each performance dimension was tested using the interaction-term approach specified in section 3.9, with significance again assessed via bootstrapped 95% confidence intervals. Table 4.6 presents the results.

Interaction Path	β (mean)	SE	95% CI	Decision
AI Adoption $\times$ IB $\rightarrow$ COST	-0.188	0.042	[-0.274, -0.109]	Ho4 rejected (significant)
AI Adoption $\times$ IB $\rightarrow$ QUAL	-0.113	0.054	[-0.208, 0.001]	Ho4 not rejected
AI Adoption $\times$ IB $\rightarrow$ DEL	-0.112	0.047	[-0.204, -0.022]	Ho4 rejected (significant)
AI Adoption $\times$ IB $\rightarrow$ FLEX	-0.105	0.056	[-0.213, 0.002]	Ho4 not rejected

Table 4.6: Bootstrapped Interaction (Moderation) Effects of Implementation Barriers

The results provide partial support for Ho4. Implementation barriers significantly and negatively moderate the relationship between AI adoption and both cost performance ($\beta = -0.188$, 95% CI excludes zero) and delivery performance ($\beta = -0.112$, 95% CI excludes zero): the positive effect of AI adoption on these two performance outcomes is measurably weaker among firms reporting higher implementation barriers. The interaction effect is directionally negative but not statistically significant for quality (95% CI = [-0.208, 0.001]) and flexibility (95% CI = [-0.213, 0.002]) outcomes, where the confidence interval narrowly includes zero. Ho4 is therefore rejected for the cost and delivery dimensions of operational performance, and not rejected for the quality and flexibility dimensions, indicating that implementation barriers, cost of acquisition, skills shortages, data quality, infrastructure, and staff resistance, condition the returns to AI adoption unevenly across performance outcomes rather than uniformly suppressing all performance gains.

4.8 Discussion of Findings

The finding that all three AI adoption dimensions significantly and positively predict all four dimensions of operational performance corroborates the broadly positive relationship reported in recent manufacturing-sector studies, including Hong, Zhong, and Um (2025) in a Chinese manufacturing sample and Al Koliby, Al-Swidi, Al-Hakimi, and Farhan (2025) in US and UK manufacturing contexts, and extends this evidence to a Nigerian, developing-economy manufacturing setting, addressing the gap identified in section 2.5. The result

is also consistent with the Nigerian-specific literature reviewed in section 2.3 (Eze, Chinedu-Eze, & Bello, 2021; Audu & Aziwe, 2025; Obi, 2024; Anetoh, 2025), which similarly reports measurable performance gains associated with AI adoption in Nigerian manufacturing, albeit unevenly across firms.

The consistently stronger path coefficients observed for AI-driven demand forecasting and inventory optimisation (DFI), relative to supplier selection and evaluation (SSE) and spend analysis and contract management (SACM), is consistent with the view advanced in the conceptual review (section 2.1) that forecasting and inventory applications represent a comparatively mature and well-diffused category of AI use in procurement, with more direct and immediate operational consequences (reduced stockouts, improved replenishment accuracy) than supplier evaluation or contract-analytics applications, whose benefits may accrue more indirectly and over a longer horizon.

The partial moderation finding, whereby implementation barriers significantly weaken the AI-performance relationship for cost and delivery outcomes but not for quality and flexibility outcomes, offers a more nuanced picture than a simple uniform-dampening hypothesis. A plausible interpretation, consistent with the Technology-Organisation-Environment framework underpinning the moderating variable (section 2.2), is that cost and delivery outcomes are more directly contingent on the technical and infrastructural conditions captured by the IB construct (cost of tools, digital infrastructure, data quality)

required for AI systems to generate timely, actionable forecasts and cost signals, whereas quality and flexibility gains may derive more from the standardisation and consistency AI-based evaluation introduces into supplier and specification decisions, a mechanism less directly dependent on infrastructure and skills availability. This finding refines, rather than contradicts, the moderating role of implementation barriers proposed in the conceptual framework (section 2.4) and identified in prior Nigerian literature (Eze et al., 2021; Badghish & Soomro, 2024).

5.0 SUMMARY, CONCLUSION AND RECOMMENDATIONS

5.1 Summary of Findings

This study empirically examined the relationship between artificial intelligence adoption in procurement and the operational performance of manufacturing firms, using primary survey data obtained from 345 procurement and operations managers in manufacturing firms registered with the Manufacturers Association of Nigeria, and analysed using Partial Least Squares Structural Equation Modelling. The measurement model demonstrated satisfactory reliability, convergent validity, and discriminant validity across all eight constructs. The structural model results show that AI-based supplier selection and evaluation, AI-driven demand forecasting and inventory optimisation, and AI-enabled spend analysis and contract management each exert a statistically significant, positive effect on all four dimensions of operational performance (cost, quality, delivery, and flexibility), with demand forecasting and inventory optimisation emerging as the strongest predictor. Implementation barriers were found to significantly weaken the AI-performance relationship for cost and delivery outcomes, but not for quality and flexibility outcomes, indicating a selective rather than uniform moderating effect.

5.2 Conclusion

The study concludes that AI adoption in procurement is significantly and positively associated with manufacturing operational performance in the Nigerian context studied, providing firm-level, developing-economy evidence that corroborates and extends findings previously reported in advanced-economy manufacturing settings (Hong, Zhong, & Um, 2025; Al Koliby, Al-Swidi, Al-Hakimi, & Farhan, 2025). All three null hypotheses concerning the direct effects of AI adoption dimensions on operational performance (Ho1, Ho2, Ho3) are rejected. The null hypothesis concerning the moderating role of implementation barriers (Ho4) is rejected for cost and delivery performance and not rejected for quality and flexibility performance, indicating that implementation barriers condition the returns to AI adoption unevenly across

operational outcomes rather than suppressing performance gains uniformly. These findings support the dynamic-capabilities interpretation of AI adoption advanced in the theoretical framework (section 2.2): AI adoption in procurement appears to translate into measurable, if moderate, operational performance gains, with the strength of that translation shaped by the technology-organisation-environment conditions captured by the implementation-barriers construct.

5.3 Recommendations

Based on the findings, the following recommendations are made. First, manufacturing firm managers should prioritise AI investment in demand forecasting and inventory optimisation applications, given that this dimension consistently produced the largest performance effects across all four outcome measures in this study, before extending investment into supplier evaluation and spend/contract analytics applications. Second, firms seeking cost and delivery performance gains from AI adoption should specifically address the implementation barriers, cost of tools, digital infrastructure, and staff technical skills, identified in this study as significant dampeners of the AI-performance relationship for these two outcomes; firms with weaker digital infrastructure or skills bases are likely to realise smaller cost and delivery gains from equivalent AI investment. Third, policymakers, including the Manufacturers Association of Nigeria and relevant government agencies, should support manufacturing-sector AI adoption through targeted investment in digital infrastructure and technical skills training, given the demonstrated role of these factors in determining the magnitude of performance returns. Fourth, given that R^2 values for the direct-effects model, while statistically significant, remain moderate (0.094 to 0.112), future research should extend the model specified in section 3.9 to include additional predictors of manufacturing operational performance, such as organisational dynamic capabilities and workforce digital skills as direct or mediating variables, to build a more complete explanatory account. Finally, given the cross-sectional design adopted in this study (section 3.1), longitudinal research is recommended to establish the direction of causality between AI adoption and operational performance with greater confidence.

REFERENCES

1. Agrawal, R., Majumdar, A., Kumar, A., & Luthra, S. (2023). Integration of artificial intelligence in sustainable manufacturing: Current status and future opportunities. *Operations Management*

- Research, 16(4), 1720–1741. <https://doi.org/10.1007/s12063-023-00400-0>
2. Al Koliby, I. S., Al-Swidi, A. K., Al-Hakimi, M. A., & Farhan, S. A. G. (2025). Building AI-enabled capabilities for improved environmental and manufacturing performance: Evidence from the US and the UK. *International Journal of Production Research*. Advance online publication.
 3. Allal-Chérif, O., Simón-Moya, V., & Ballester, A. C. C. (2021). Intelligent purchasing: How artificial intelligence can redefine the purchasing function. *Journal of Business Research*, 124, 69–76. <https://doi.org/10.1016/j.jbusres.2020.11.050>
 4. Anetoh, J. C. (2025). The power of innovation: Achieving sustainable performance in cement manufacturing industry in Nigeria through artificial intelligence. *World Journal of Innovation and Modern Technology*.
 5. Audu, Y. P., & Aziwe, N. I. (2025). Artificial intelligence and the performance of manufacturing firms in North-Central Nigeria: Reward system as the moderator. *International Journal of Research and Innovation in Social Science*, 9(1), 1738–1755.
 6. Badghish, S., & Soomro, Y. A. (2024). Artificial intelligence adoption by SMEs to achieve sustainable business performance: Application of technology–organization–environment framework. *Sustainability*, 16(5), 1864. <https://doi.org/10.3390/su16051864>
 7. Bag, S., Pretorius, J. H. C., Gupta, S., & Dwivedi, Y. K. (2021). Role of institutional pressures and resources in the adoption of big data analytics powered artificial intelligence, sustainable manufacturing practices and circular economy capabilities. *Technological Forecasting and Social Change*, 163, 120420. <https://doi.org/10.1016/j.techfore.2020.120420>
 8. Cochran, W. G. (1977). *Sampling techniques* (3rd ed.). John Wiley & Sons.
 9. Cronbach, L. J. (1951). Coefficient alpha and the internal structure of tests. *Psychometrika*, 16(3), 297–334. <https://doi.org/10.1007/BF02310555>
 10. Edijala, D., Rakshit, S., & Vajjhala, N. R. (2024). Applications of artificial intelligence in public procurement: Case study of Nigeria. In S. Kautish, P. Chatterjee, D. Pamucar, N. Pradeep, & D. Singh (Eds.), *Computational intelligence for modern business systems* (pp. 379–393). Springer. https://doi.org/10.1007/978-981-99-5354-7_27
 11. Eze, S. C., Chinedu-Eze, V. C., & Bello, O. S. (2021). Factors influencing the adoption of AI in the Nigerian manufacturing industry: An innovation diffusion theory perspective. *Journal of Business & Industrial Marketing*, 36(6), 926–943. <https://doi.org/10.1108/JBIM-09-2019-0409>
 12. Hong, S., Zhong, D., & Um, K. (2025). The impact of artificial intelligence (AI) adoption on operational performance in manufacturing. *Journal of Manufacturing Technology Management*, ahead-of-print. <https://doi.org/10.1108/JMTM-03-2025-0227>
 13. Liu, D., & Son, S. (2024). Exploring the impact mechanism of collaborative robot on manufacturing firm performance: A dynamic capability perspective. *Sustainable Futures*, 8, 100262. <https://doi.org/10.1016/j.sftr.2024.100262>
 14. Mikalef, P., & Gupta, M. (2020). Artificial intelligence capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance. *Information & Management*, 58(3), 103434. <https://doi.org/10.1016/j.im.2020.103434>
 15. Obi, A. V. (2024). Management of artificial intelligence and the performance of manufacturing firms in Enugu State, Nigeria. *Tec Empresarial*, 19(1).
 16. Yamane, T. (1967). *Statistics: An introductory analysis* (2nd ed.). Harper and Row.