

Artificial Intelligence and Buyer–Supplier Relationships in Procurement: Evidence from TECNO Mobile Nigeria

Dennis Ejike Onyishi¹; Confidence Ekeutomhinye²; Linda Chinelo Agbasianya³; Chima Roland Obiora⁴; Abdulquddus Olanrewaju Abdulyaqeen⁵ and Ayo David Adeyemi⁶

¹University of Nigeria, Nsukka, Nigeria. ²Department of Public Administration, University of Benin, Nigeria.

³Department of Microbiology, Faculty of Science, Obafemi Awolowo University, Nigeria. ⁴Department of Computer Science, Faculty of Physical Sciences, University of Nigeria, Nsukka, Nigeria. ⁵Department of Computer Science, Faculty of Computing and Informatics, University of Lagos, Nigeria. ⁶Faculty of Science, Business and Enterprise, University of Chester, Exton Park, Chester CH1 4BJ, United Kingdom.

Corresponding author: dennis.ejike.onyishi@gmail.com

DOI: <https://doi.org/10.62154/ajmbr.2026.023.01039>

Abstract

This study investigates the influence of Artificial Intelligence (AI) applications on buyer–supplier relationship quality in Nigeria's mobile manufacturing sector, with specific reference to TECNO Mobile Nigeria. Drawing on the Commitment-Trust Theory of Relationship Marketing (Morgan & Hunt, 1994), the study operationalises AI through three proxies: Predictive Analytics (PA), Automation of Processes (AP), and AI Risk Management (AIR). A survey research design was adopted, and structured questionnaires were administered to 250 employees and supply chain partners purposively selected from TECNO Mobile's procurement, logistics, IT, and supplier management functions. Data were analysed using descriptive statistics (frequencies, means, standard deviations) and one-sample t-tests benchmarked against the scale's neutral midpoint ($\mu_0 = 3.00$). All three null hypotheses were rejected at $p < 0.001$. Predictive Analytics recorded an aggregate mean of 3.88 (SD = 0.34; $t(249) = 40.53$), Automation of Processes 3.91 (SD = 0.36; $t(249) = 40.05$), and AI Risk Management 3.92 (SD = 0.36; $t(249) = 40.47$), all significantly above the neutral midpoint. Findings confirm that respondents perceive each AI dimension as positively and meaningfully contributing to trust, efficiency, transparency, and long-term relational stability with suppliers. The study contributes empirical evidence from an under-studied domain in the AI-supply chain literature, Nigeria's mobile manufacturing sector, and offers practical guidance for practitioners and policymakers pursuing AI-enabled supply chain transformation in emerging economies.

Keywords: Artificial Intelligence, Predictive Analytics, Process Automation, AI Risk Management, Buyer–Supplier Relationships, Commitment-Trust Theory, Supply Chain Management, Nigeria, TECNO Mobile.

Introduction

The integration of Artificial Intelligence (AI) into supply chain management (SCM) has emerged as one of the most consequential developments in contemporary operations management. By enabling real-time data processing, predictive decision-making, and

intelligent automation, AI has transformed traditional supply chains into adaptive, resilience-oriented ecosystems (Wamba et al., 2023; Wamba et al., 2020; Ivanov, 2023). A particularly salient outcome of AI-enabled SCM is the reconfiguration of buyer–supplier relationships (BSRs), the relational and operational interactions between purchasing organisations and their supply partners that determine supply chain performance, trust, and long-term stability (Lambert, 2019).

Globally, the business case for AI in SCM is well established. Gartner (2024) reports that a majority of manufacturers now deploy AI-driven solutions for demand forecasting, supplier performance analysis, and inventory optimisation. Major multinationals have embedded AI into their procurement and logistics systems to monitor supplier compliance, reduce costs, and enhance operational resilience (Ivanov & Dolgui, 2022; Riad et al., 2024). The disruptions of the past decade also exposed the limits of reactive, linear supply models, and this accelerated the adoption of AI-enabled resilience frameworks that anticipate disruptions and optimise alternative sourcing (Baryannis, Validi, Dani, & Antoniou, 2023).

In Africa, AI adoption in SCM has gained momentum, supported by the continent's expanding digital economy (World Bank, 2024). Studies from Kenya, South Africa, Ghana, and Morocco increasingly demonstrate that AI-driven forecasting, supplier evaluation, and resource-efficiency tools can improve supply chain visibility and resilience even under significant infrastructural constraints (Daraojimba et al., 2024; Manu et al., 2024; Peprah et al., 2025). Nigeria, Africa's largest economy, has articulated this ambition through its National Artificial Intelligence Strategy (NITDA, 2023). Yet empirical evidence linking AI adoption to BSR quality in the Nigerian manufacturing context remains sparse.

Nigeria's mobile manufacturing sector, anchored by brands such as TECNO, Infinix, and itel, serves a large and fast-growing smartphone user base and is among the fastest-growing consumer electronics markets in Africa (GSMA, 2024). The sector's supply chains are, however, constrained by currency instability, logistical bottlenecks, and infrastructural deficits (Ifere et al., 2022). These conditions make efficient, trust-based buyer–supplier interactions not merely desirable but operationally critical. TECNO Mobile Nigeria, as the sector leader, presents an important empirical site for examining whether AI adoption can meaningfully enhance BSR quality under such conditions.

Existing studies on AI and BSRs have largely focused on technologically advanced economies, with limited integration of multiple AI dimensions within a single relational model applicable to emerging markets (Al-Shboul, 2024; Osewe et al., 2026). This study addresses that gap by empirically examining three AI proxies, Predictive Analytics, Automation of Processes, and AI Risk Management, and their perceived influence on BSR outcomes at TECNO Mobile Nigeria. It is grounded in the Commitment-Trust Theory of Relationship Marketing (Morgan & Hunt, 1994), which explains how relational mechanisms of trust and commitment mediate the exchange behaviours this study measures.

Statement of the Problem

Despite the well-documented global business case for AI-enabled supply chain management, Nigerian manufacturing firms, and mobile handset manufacturers in particular, continue to operate buyer–supplier relationships under conditions of information asymmetry, delayed communication, inconsistent quality assurance, and limited algorithmic governance. Where AI tools such as predictive analytics, workflow automation, and risk-monitoring systems have been introduced, their perceived contribution to the relational dimensions of supply chain performance (trust, transparency, confidence, and long-term stability) has rarely been examined using a theory-driven, quantitative approach specific to the Nigerian mobile manufacturing context.

Furthermore, much of the existing AI-supply chain literature either treats AI as a single undifferentiated construct or restricts its theoretical grounding to adoption-oriented frameworks such as the Technology–Organisation–Environment (TOE) model, which explain why firms adopt AI but not how that adoption translates into relational outcomes between buyers and suppliers. This leaves a conceptual and empirical gap: it is not clear, from a relationship-marketing standpoint, how strongly Nigerian supply chain practitioners perceive specific AI capabilities as building the trust and commitment on which durable buyer–supplier relationships depend. This study was designed to close that gap by empirically testing, through the lens of the Commitment-Trust Theory, whether Predictive Analytics, Automation of Processes, and AI Risk Management are perceived to significantly and positively influence buyer–supplier relationship quality at TECNO Mobile Nigeria.

Objectives of the Study

The general objective of this study is to investigate the influence of Artificial Intelligence applications on buyer–supplier relationship quality in Nigeria's mobile manufacturing sector, with specific reference to TECNO Mobile Nigeria. The specific objectives are to:

- i. examine the effect of Predictive Analytics on trust and reliability in TECNO Mobile Nigeria's buyer–supplier relationships;
- ii. assess the ways in which Automation of Processes improves efficiency, transparency, and coordination between TECNO Mobile Nigeria and its suppliers; and
- iii. determine how AI Risk Management contributes to confidence and long-term stability in TECNO Mobile Nigeria's buyer–supplier relationships.

Research Questions

In line with the objectives above, the study addresses the following research questions:

- i. How does Predictive Analytics influence trust and reliability in TECNO Mobile Nigeria's buyer–supplier relationships?
- ii. In what ways does Automation of Processes improve efficiency, transparency, and coordination between TECNO Mobile Nigeria and its suppliers?

- iii. How does AI Risk Management contribute to confidence and long-term stability in TECNO Mobile Nigeria's buyer–supplier relationships?

Research Hypotheses

The study tests the following null hypotheses, each evaluated against the scale's neutral midpoint ($\mu_0 = 3.00$):

H01: Predictive Analytics has no significant influence on trust and reliability in TECNO Mobile Nigeria's buyer–supplier relationships.

H02: Automation of Processes does not significantly improve efficiency, transparency, and coordination between TECNO Mobile Nigeria and its suppliers.

H03: AI Risk Management does not significantly contribute to confidence and long-term stability in TECNO Mobile Nigeria's buyer–supplier relationships.

Significance of the Study

This study is relevant to several groups of stakeholders. For practitioners and managers within TECNO Mobile Nigeria and comparable mobile manufacturing firms, the findings provide an evidence base for prioritising investment across predictive analytics, process automation, and AI governance as levers for strengthening supplier relationships. For Nigerian policymakers, particularly the National Information Technology Development Agency (NITDA), the study offers empirical grounding for sector-specific AI governance guidelines that can support trustworthy AI adoption in manufacturing supply chains. For suppliers and supply chain partners, the study points to the relational value of transparent, well-governed AI systems, which may inform how they engage with AI-enabled buyers. For academics, the study extends the Commitment-Trust Theory into an AI-enabled, emerging-economy manufacturing context, offering a replicable empirical framework linking specific AI capabilities to relationship-quality outcomes that can be extended to other sectors, firms, and African country contexts.

Scope of the Study

The study is delimited to TECNO Mobile Nigeria, a leading mobile handset manufacturer operating within Nigeria's consumer electronics supply chain. Content-wise, the study is restricted to three AI proxies (Predictive Analytics, Automation of Processes, and AI Risk Management) and their perceived influence on buyer–supplier relationship quality, as opposed to firm-level financial or operational performance outcomes. The study population comprises 320 employees and supply chain partners directly involved in procurement, logistics, production planning, supplier management, and IT systems integration at TECNO Mobile Nigeria, from which a purposively selected sample of 250 respondents was drawn. The study adopts a cross-sectional survey design and does not track changes in perceptions over time; longitudinal and multi-firm extensions are identified as directions for future research in Section 5

Theoretical Framework and Literature Review

Conceptual Review

Artificial Intelligence in Supply Chain Management

Artificial Intelligence (AI) in supply chain management refers to the application of machine learning, natural language processing, and intelligent automation technologies to support data-driven decision-making, forecasting, and process execution across procurement, logistics, and supplier-facing functions (Ivanov, 2023; Daios et al., 2025). Rather than a single technology, AI in SCM is best understood as a portfolio of capabilities, spanning predictive modelling, robotic process automation, and governance and risk-monitoring tools, that collectively reconfigure how buying organisations plan, communicate with, and evaluate their suppliers (Riad et al., 2024). This conceptualisation underpins the present study's decision to operationalise AI through three distinct but complementary proxies rather than as an undifferentiated construct.

Predictive Analytics

Predictive Analytics (PA) is the use of historical and real-time data, statistical algorithms, and machine learning techniques to forecast future events, supplier behaviour, and potential supply chain disruptions (Schoenherr & Speier-Pero, 2022). In a buyer–supplier context, PA is typically applied to demand forecasting, supplier performance scoring, and early-warning detection of delivery or quality risks, enabling buying organisations to shift from reactive to proactive supplier management (Nzeako et al., 2024; Nweje et al., 2025).

Automation of Processes

Automation of Processes (AP) refers to the deployment of robotic process automation (RPA), intelligent workflow engines, and autonomous transaction systems to execute routine procurement and logistics tasks with minimal human intervention (Zdravković et al., 2021). Within SCM, process automation is associated with reduced cycle times, fewer manual errors, and improved consistency in supplier-facing transactions such as purchase order processing, invoice matching, and shipment tracking (Lodhi et al., 2024).

AI Risk Management

AI Risk Management (AIR) encompasses the governance frameworks, algorithmic transparency mechanisms, data-privacy safeguards, and continuous monitoring processes that organisations put in place to ensure AI-driven decisions remain fair, explainable, and accountable (Baryannis, Validi, Dani, & Antoniou, 2023; Cobbe, Veale, & Singh, 2023). In supplier-facing contexts specifically, AI risk governance addresses concerns such as algorithmic bias in supplier scoring, the trustworthiness of automated decisions, and the protection of shared operational data (Ahangar et al., 2025).

Buyer–Supplier Relationships

Buyer–supplier relationships (BSRs) are the relational and operational interactions between purchasing organisations and their supply partners that determine trust, coordination, and long-term supply chain performance (Lambert, 2019). Contemporary supply chain scholarship increasingly frames BSR quality along relational dimensions, including trust, commitment, satisfaction, and collaborative behaviour, rather than purely transactional or contractual terms, since collaborative activities such as information sharing and joint effort have been shown to generate the trust and commitment that ultimately drive relationship performance (Nyaga, Whipple, & Lynch, 2010). This relational conceptualisation of BSR quality is the outcome construct that the present study measures across its three AI proxies.

Theoretical Framework

Commitment-Trust Theory of Relationship Marketing

This study is anchored on the Commitment-Trust Theory (CTT) of relationship marketing, originally advanced by Morgan and Hunt (1994) in their seminal *Journal of Marketing* article. CTT was selected over adoption-oriented frameworks because the outcome variables this study measures (trust and reliability, efficiency and transparency, and confidence and long-term stability) are, definitionally, the relational constructs at the centre of CTT itself. This makes it a substantially closer theoretical fit to the study's research questions than a technology-adoption lens such as the Technology–Organisation–Environment framework, which explains why firms adopt a technology but is silent on the relational mechanisms through which that technology then shapes ongoing exchange behaviour.

Morgan and Hunt (1994) theorised that successful relationship marketing, the establishing, developing, and maintaining of successful relational exchanges, depends fundamentally on two mediating variables: relationship commitment and trust. Their Key Mediating Variable (KMV) model proposes that five antecedent conditions (relationship termination costs, relationship benefits, shared values, communication, and opportunistic behaviour) act upon commitment and trust, which in turn mediate five consequent outcomes: acquiescence, propensity to leave the relationship, cooperation, functional conflict, and decision-making uncertainty. The theoretical contribution of the KMV model was to demonstrate, using data from automobile tyre retailers and their suppliers, that trust and commitment, rather than satisfaction or dependence alone, are the pivotal psychological states that determine whether an exchange relationship endures. Firms that are trusted and to whom their partners are committed experience greater acquiescence to reasonable requests, lower propensity for partners to exit the relationship, higher levels of cooperation, more constructive conflict resolution, and reduced uncertainty in decision-making. These outcomes map closely onto the efficiency, transparency, confidence, and stability dimensions this study investigates.

Since its original formulation, CTT has been extensively validated and extended within business-to-business (B2B) and supply chain contexts specifically. Crotts et al. (2001)

applied a trust-commitment model directly to buyer–supplier relationships, showing that a cooperative, trust-based orientation between wholesale suppliers and their buyers displaced the older adversarial transaction model. Wu et al. (2012) tested the fit of commitment-trust theory in high-technology supply chain partnerships in Taiwan, confirming that higher levels of trust facilitate better interaction and reduce uncertainty between exchange partners, while higher commitment increases value benefits and cooperation efficiency. Nyaga, Whipple, and Lynch (2010) extended the model further by demonstrating, across independent buyer and supplier samples, that collaborative activities, including information sharing, joint relationship effort, and dedicated investments, are themselves antecedents that build the trust and commitment which subsequently drive satisfaction and performance, with the specific pathways differing modestly between buyer and supplier perspectives. More recently, Duan et al. (2024) revisited trust-commitment theory in the context of blockchain-enabled sustainable sourcing, finding that transparent, verifiable digital governance mechanisms, conceptually analogous to the AI risk-management proxy in this study, significantly strengthen buyer trust even as they interact with commitment in complex ways. This confirms that digitally mediated transparency is now a recognised antecedent within the CTT nomological network.

The theory has also attracted refinement rather than wholesale replacement. Brown et al. (2019) re-examined the presumed one-directional causal path from trust to commitment across three datasets, including Morgan and Hunt's original data, and found that while trust does enhance commitment, commitment can, under certain conditions, also erode trust. This is a reciprocal dynamic that this study's cross-sectional design cannot itself disentangle but which is acknowledged as a boundary condition in the limitations discussed in Section 5. This body of refinement work does not undermine CTT's core proposition; rather, it strengthens its applicability by clarifying that trust and commitment operate as an interdependent relational core rather than a simple linear chain.

Applied to the present study, the Commitment-Trust Theory provides the following theoretical mapping. Predictive Analytics, Automation of Processes, and AI Risk Management are conceptualised as organisational-level antecedent conditions, functionally analogous to Morgan and Hunt's communication and shared-values antecedents, through which TECNO Mobile Nigeria signal's reliability, reduces information asymmetry, and demonstrates fair and accountable conduct toward its suppliers. Predictive Analytics, by enabling proactive rather than reactive supplier management, reduces the uncertainty that CTT identifies as a key relational cost, thereby building trust. Automation of Processes, by standardising and de-personalising routine transactions, reduces the perceived opportunism and inconsistency that erode trust, while simultaneously generating the transactional efficiency and transparency that CTT associates with cooperative, low-conflict exchange. AI Risk Management, by embedding governance, explainability, and accountability into AI-driven decisions, most directly addresses the

antecedent conditions Morgan and Hunt identified as central to commitment, namely, the sense that a partner is trustworthy enough to warrant continued investment in the relationship. Collectively, this theoretical framing predicts that all three AI proxies should be positively associated with the relational outcomes measured in this study, and it is this prediction that the three research hypotheses in Section 1 formally test.

Empirical Review

Predictive Analytics and Buyer–Supplier Trust

A growing body of empirical work links predictive analytics to improved supplier relationship outcomes. Nzeako et al. (2024) reviewed the role of AI-driven predictive analytics in optimising IT-industry supply chains, reporting that predictive tools meaningfully enhance demand forecasting, supplier selection, and risk management, though they note persistent challenges around data quality and skilled-personnel availability that can moderate these benefits. Similarly, Nweje et al. (2025) found that AI-driven predictive tools for demand forecasting and inventory optimisation produced substantial reductions in holding costs and improved lead times across the case studies reviewed, which supports the proactive-management mechanism through which predictive analytics is theorised to build supplier trust. Within the broader African context, Daraojimba et al. (2024) compared AI-driven supply chain optimisation trends between the United States and African firms. They found that while African adoption of predictive analytics remains more gradual due to infrastructural constraints, the direction of effect, improved visibility and reduced waste, mirrors that observed in more digitally mature markets, which supports the relevance of predictive analytics research to the Nigerian context examined in this study.

Automation of Processes and Relational Efficiency

Empirical evidence on process automation similarly points toward improved buyer–supplier coordination. Zdravković et al. (2021) reviewed AI-enabled enterprise information systems in manufacturing and identified automation-driven decision-making and logic-based systems as central to improved supply chain and customer relationship management functions. Adenekan et al. (2024) similarly reviewed AI-driven supply chain optimisation integrated with ERP systems, concluding that automation of demand forecasting, inventory management, and cross-functional data exchange improves forecasting accuracy, reduces lead times, and enables the real-time visibility that underlies coordinated buyer–supplier interaction. Consistent with this pattern, survey evidence from large Nigerian manufacturing firms similarly links automation adoption to measurable gains in operational efficiency and competitiveness, while identifying implementation cost and workforce readiness as the principal constraints on wider adoption.

AI Risk Management and Relational Stability

Governance and risk-management dimensions of AI adoption have also received growing empirical attention. Ahangar et al. (2025) surveyed AI trustworthiness in manufacturing, identifying transparency, fairness, robustness, and accountability as the core principles that toolkits and governance frameworks must operationalise to build stakeholder trust in AI-driven decisions. These principles are directly analogous to the AI Risk Management construct measured in this study. Vann Yaroson et al. (2025) examined human-AI collaboration in supply chain outcomes and found that responsible AI practices mediate the relationship between collaborative AI use and supply chain wellbeing, confirming that governance quality, rather than AI use in isolation, is what translates into positive relational and performance outcomes. In the sustainable-sourcing domain, Duan et al. (2024) demonstrated that blockchain-based governance mechanisms, a close technological cousin of AI risk-management systems, significantly enhance buyer trust in supplier relationships. This lends further empirical support to the theoretical link this study draws between AI governance and relational stability.

AI, Trust, and Buyer–Supplier Relationships in African and Nigerian Manufacturing

Within the African manufacturing literature more broadly, Al-Shboul (2024) found that AI system adoption significantly and directly improves production management and supply chain performance among pharmaceutical manufacturing firms across the MENA region, with strategic supplier reliability emerging as a key mediating pathway. This finding is structurally consistent with this study's proposition that AI proxies operate through relational, trust-based mechanisms rather than through technology alone. Manu et al. (2024) examined the impact of AI on resource efficiency in West African manufacturing and found that AI-driven technologies significantly improve resource efficiency, moderated positively by regulatory environment and employee training and adaptation. This suggests that the institutional and governance context, echoing the AI Risk Management construct, shapes how effectively AI capabilities translate into operational and relational benefits in African settings. Most recently, a systematic review of AI's role in supplier relationship management decision-making synthesised evidence across manufacturing, construction, banking, and enterprise procurement contexts, reporting substantial improvements in supply chain performance, resilience, and risk-detection accuracy attributable to AI, while also identifying legacy-system incompatibility, data-quality deficits, and workforce digital-literacy gaps as the principal barriers suppressing fuller adoption of AI's highest-impact supplier relationship management roles (Osewe et al., 2026). These barriers are highly consistent with the infrastructural constraints (Ifere et al., 2022) that frame this study's Nigerian mobile manufacturing context.

Summary of Literature Review and Gap in Knowledge

The reviewed literature confirms that AI applications, spanning predictive analytics, process automation, and risk governance, are consistently associated with improved supply chain performance, efficiency, and, increasingly, relational trust across both advanced and emerging economies. However, three gaps remain. First, the large majority of empirical studies either examine AI as a single undifferentiated construct or focus on isolated dimensions (typically predictive analytics or automation alone), rather than integrating multiple AI proxies within a single relational model. Second, studies that do adopt a relational or theory-driven lens have rarely applied the Commitment-Trust Theory specifically to AI-enabled buyer–supplier relationships, more commonly relying on adoption-oriented frameworks such as TOE or the resource-based view, which explain adoption decisions but not relational consequences. Third, empirical evidence from Nigeria's mobile manufacturing sector, a fast-growing but infrastructurally constrained segment of Africa's largest economy, remains especially sparse, with most African AI-supply chain studies concentrated in food and beverage, pharmaceutical, or general manufacturing contexts. This study addresses all three gaps by empirically testing, through the Commitment-Trust Theory, the perceived influence of three distinct AI proxies (Predictive Analytics, Automation of Processes, and AI Risk Management) on buyer–supplier relationship quality at TECNO Mobile Nigeria

Methodology

Research Design and Setting

A quantitative survey research design was adopted. The study was conducted at TECNO Mobile Nigeria, a leading mobile handset manufacturer operating within Nigeria's growing consumer electronics supply chain. The study population comprised all employees and supply chain partners directly involved in procurement, logistics, production planning, supplier management, and IT systems integration at TECNO Mobile Nigeria, totalling 320 individuals (TECNO Mobile HR Records, August 2024).

Sampling

Sample size was determined using the Yamane (1967) formula at an 8%5% margin of error, yielding a minimum required sample of $n = 178$. Purposive sampling was employed to select participants with direct knowledge of and experience in AI-enabled supply chain processes, ensuring that responses reflected informed, practitioner-level perceptions. A total of 250 valid, fully completed responses were obtained and used for analysis, exceeding the minimum threshold. Ethical clearance for the study was obtained and Participation was voluntary, and informed consent was obtained from all respondents prior to questionnaire administration, with assurances of anonymity and confidentiality.

Instrument

Data were collected using a structured questionnaire comprising two sections. Section A captured five demographic variables (age group, gender, position, years of experience, educational qualification). Sections B–D measured respondents' agreement with 15 Likert-scale statements (five per construct) covering Predictive Analytics (PA), Automation of Processes (AP), and AI Risk Management (AIR). All items were anchored on a five-point scale: Strongly Agree (5) to Strongly Disagree (1). Item wording was adapted from validated instruments in the AI and SCM literature (Wamba, Queiroz, & Trinchera, 2023; Schoenherr & Speier-Pero, 2022; Baryannis, Validi, Dani, & Antoniou, 2023).

Analysis

Descriptive statistics (frequencies, percentages, means, standard deviations) were computed for all items and aggregate construct scores. A mean score of ≥ 3.50 was interpreted as 'Agreed' on the five-point scale, consistent with the Likert-score interpretation convention. Each research hypothesis was evaluated using a one-sample t-test, comparing the construct's aggregate mean against the scale's neutral midpoint ($\mu_0 = 3.00$), at a 5% level of significance. This approach is appropriate for perception-based instruments in which item wording embeds the hypothesised relationship, as the instrument in this study measures agreement with statements such as 'Predictive analytics improves trust and reliability between TECNO Mobile and its suppliers,' so that rejecting $\mu = 3.00$ in favour of $\mu > 3.00$ directly tests the hypothesis that respondents perceive the stated effect to be present. Although each hypothesis is framed directionally (predicting a positive relational effect), a two-tailed test was retained as the more conservative option: it does not presuppose the direction of the effect and therefore applies a stricter significance threshold than a one-tailed alternative would, which strengthens confidence in the substantive interpretation of the results reported in Section 4. All analyses were conducted using Python (pandas, scipy.stats).

Data Presentation, Analysis and Interpretation

Two hundred and fifty (250) valid, fully completed responses were retrieved and analysed, exceeding the minimum sample of 178 determined via the Yamane (1967) formula. Respondents were predominantly aged 25–34 (40.0%) and 35–44 (30.4%), 56.8% male, and largely holders of a Bachelor's (46.8%) or Master's (34.4%) degree, with the majority (68.4%) having more than one year of relevant supply chain experience. Respondents spanned procurement, logistics, operations, IT/analytics, and supplier-relationship roles, consistent with the purposive sampling strategy targeting staff with direct exposure to AI-enabled supply chain processes. Table 1 summarises the sample profile; the results are then presented by research question, followed by formal hypothesis testing.

Table 1: Demographic Characteristics of Respondents (n = 250)

Variable	Category	n	%
Age Group	18–24	12	4.8
	25–34	100	40.0
	35–44	76	30.4
	45–54	50	20.0
	55+	12	4.8
Gender	Male	142	56.8
	Female	108	43.2
Experience	< 1 year	17	6.8
	1–5 years	96	38.4
	6–10 years	75	30.0
	10–15 years	34	13.6
	> 15 years	28	11.2
Education	OND/HND	19	7.6
	Bachelor's	117	46.8
	Master's	86	34.4
	Ph.D.	28	11.2

Source: Field Survey, 2026

Research Question One: Effect of Predictive Analytics on Trust and Reliability

Research Question One asked how Predictive Analytics influences trust and reliability in TECNO Mobile Nigeria's buyer–supplier relationships. Table 2 presents the descriptive results for the five Predictive Analytics (PA) items.

Table 2: Descriptive Statistics for Predictive Analytics (PA)

Item	SA %	A %	UD %	D/SD %	Mean	SD
PA1: Improves trust & reliability	19.6	51.6	23.2	5.6	3.84	0.82
PA2: Enables proactive supplier management	20.0	51.6	23.2	5.2	3.86	0.81
PA3: Anticipates delivery delays & risks	26.0	51.6	19.2	3.2	3.99	0.80
PA4: Enhances collaboration & confidence	22.8	48.0	23.6	5.6	3.87	0.86
PA5: Strengthens long-term relationships	17.2	55.6	23.2	4.0	3.85	0.78
Grand Mean / SD					3.88	0.34

Source: Field Survey, 2026

All five PA items recorded mean scores above the 3.50 agreement threshold, with the highest agreement on the item measuring anticipation of delivery delays and risk mitigation (Mean = 3.99, SD = 0.80). The aggregate PA score was 3.88 (SD = 0.34), indicating that respondents generally perceive predictive analytics as improving trust and reliability in

TECNO Mobile's supplier relationships. This directly answers Research Question One in the affirmative.

Research Question Two: Effect of Automation of Processes on Efficiency, Transparency, and Coordination

Research Question Two asked in what ways Automation of Processes improves efficiency, transparency, and coordination between TECNO Mobile and its suppliers. Table 3 presents the descriptive results for the five Automation of Processes (AP) items.

Table 3: Descriptive Statistics for Automation of Processes (AP)

Item	SA %	A %	UD %	D/SD %	Mean	SD
AP1: Improves procurement efficiency	24.8	54.4	17.2	3.6	4.00	0.78
AP2: Reduces errors & enhances transparency	21.2	50.0	24.0	4.8	3.85	0.86
AP3: Facilitates timely communication	20.4	52.4	24.0	3.2	3.90	0.75
AP4: Increases consistency & predictability	22.4	51.6	22.4	3.6	3.92	0.79
AP5: Contributes to long-term stability	22.4	48.8	24.4	4.4	3.87	0.85
Grand Mean / SD					3.91	0.36

Source: Field Survey, 2026

The item measuring improved procurement and workflow efficiency recorded the highest mean (4.00, SD = 0.78), and all five items exceeded the 3.50 threshold. The aggregate AP score was 3.91 (SD = 0.36), indicating that respondents perceive automation as improving efficiency, reducing errors, and strengthening communication and coordination with suppliers. This directly answers Research Question Two in the affirmative.

Research Question Three: Effect of AI Risk Management on Confidence and Long-Term Stability

Research Question Three asked how AI Risk Management contributes to confidence and long-term stability in TECNO Mobile's buyer–supplier relationships. Table 4 presents the descriptive results for the five AI Risk Management (AIR) items.

Table 4: Descriptive Statistics for AI Risk Management (AIR)

Item	SA %	A %	UD %	D/SD %	Mean	SD
AIR1: Enhances trust & confidence	20.0	56.4	20.0	3.6	3.91	0.79
AIR2: Data privacy improves cooperation	21.6	48.8	23.6	6.0	3.85	0.86

Item	SA %	A %	UD %	D/SD %	Mean	SD
AI R3: Transparent AI reduces conflicts	22.0	51.6	20.8	5.6	3.89	0.83
AI R4: Risk monitoring strengthens accountability	22.8	53.2	21.2	2.8	3.94	0.81
AI R5: Promotes reliability in performance	23.6	56.8	16.4	3.2	3.99	0.78
Grand Mean / SD					3.92	0.36

Source: Field Survey, 2026

The item measuring AI risk management's contribution to supplier performance reliability recorded the highest mean (3.99, SD = 0.78), and all five items exceeded the 3.50 threshold. The aggregate AIR score was 3.92 (SD = 0.36), the highest of the three constructs, indicating that respondents perceive AI risk governance, including data privacy, transparency, and ethical compliance, as building confidence and long-term stability in supplier relationships. This directly answers Research Question Three in the affirmative.

Hypothesis Testing

The three null hypotheses formulated in line with the study's objectives were tested using one-sample t-tests, comparing each construct's aggregate mean against the scale's neutral midpoint (test value = 3.00) at $\alpha = 0.05$ (critical $t(249) \approx 1.96$, two-tailed). Table 5 summarises the results.

Table 5: One-Sample t-Test Results for Hypothesis Testing (Test Value = 3.00)

Hypothesis	Construct	Mean	SD	t-value	df	p-value
Ho1 (Rejected)	Predictive Analytics → Trust & Reliability	3.88	0.34	40.53	249	0.000
Ho2 (Rejected)	Automation of Processes → Efficiency & Transparency	3.91	0.36	40.05	249	0.000
Ho3 (Rejected)	AI Risk Management → Confidence & Stability	3.92	0.36	40.47	249	0.000

Source: Field Survey, 2026

Ho1 (Predictive Analytics has no significant influence on trust and reliability) was rejected: $t(249) = 40.53$, $p = 0.000$. Ho2 (Automation of Processes does not significantly improve efficiency, transparency, and coordination) was rejected: $t(249) = 40.05$, $p = 0.000$. Ho3 (AI Risk Management does not significantly contribute to confidence and long-term stability) was rejected: $t(249) = 40.47$, $p = 0.000$. As all three calculated t-values (40.05–40.53) substantially exceed the critical value of 1.96, all three null hypotheses are rejected in favour of their respective alternate hypotheses, confirming that Predictive Analytics, Automation of Processes, and AI Risk Management each exert a statistically significant, positive influence on buyer–supplier relationship quality at TECNO Mobile Nigeria.

Discussion

The findings support the proposition that AI applications, operationalised through predictive analytics, process automation, and risk management, positively and significantly shape buyer–supplier relationship quality in Nigeria's mobile manufacturing sector. Read through the Commitment-Trust Theory (Morgan & Hunt, 1994), these results are consistent with, and extend, prior work in both global and African supply chain contexts.

The significant positive perception of Predictive Analytics (Mean = 3.88) is consistent with the broader empirical literature on AI-driven forecasting and supplier trust, including Nzeako et al.'s (2024) finding that predictive analytics meaningfully improves demand forecasting and supplier selection, and Nweje et al.'s (2025) evidence that predictive tools reduce holding costs and improve lead times. Within the Commitment-Trust framework, predictive analytics enhances the quality of the exchange by reducing the decision-making uncertainty that Morgan and Hunt (1994) identify as a direct consequence of low trust. Buyers who can anticipate supplier difficulties signal reliability and commitment, which CTT predicts should trigger reciprocal cooperative engagement from suppliers.

The significant finding for Automation of Processes (Mean = 3.91) supports the wider evidence base linking AI-driven automation to operational consistency and supplier interaction quality (Zdravković et al., 2021; Adenekan et al., 2024). Process automation reduces the friction and variability inherent in manual procurement interactions. Within the Commitment-Trust framework, this standardisation lowers the perceived opportunism that erodes trust, while the resulting transparency and consistency in transaction handling are precisely the conditions under which CTT predicts functional, rather than destructive, conflict resolution and greater cooperation between exchange partners.

The highest aggregate mean, recorded for AI Risk Management (Mean = 3.92), indicates that respondents perceive governance, transparency, and ethical AI deployment as the most valued dimension of AI for sustaining buyer–supplier relationships. This finding resonates with Ahangar et al.'s (2025) emphasis on transparency, fairness, and accountability as prerequisites for AI trustworthiness in manufacturing, and with Duan et al.'s (2024) finding that verifiable digital governance mechanisms significantly strengthen buyer trust in sustainable sourcing relationships. Within CTT, AI Risk Management maps most directly onto the antecedent conditions Morgan and Hunt (1994) identified as central to commitment, namely the sense that a partner is trustworthy enough to warrant continued relational investment, which is consistent with this construct recording the highest mean of the three. This matters for an emerging-economy context where regulatory and governance frameworks are still maturing: the responsible governance of AI systems is not peripheral to supply chain performance but central to it.

The closeness of the three-aggregate means (3.88 to 3.92) also deserves attention. It suggests that at TECNO Mobile Nigeria, the three AI dimensions are perceived as comparably important, with no single mechanism overshadowing the others. This is consistent with the Commitment-Trust Theory's emphasis that sustained relational quality

depends on consistency across multiple dimensions of exchange fairness (communication, reduced opportunism, and demonstrated reliability) rather than excellence in any one antecedent alone (Morgan & Hunt, 1994; Brown et al., 2019).

The study's findings also carry implications for the broader AI-SCM literature in emerging markets. Most prior work has examined individual AI dimensions in isolation or in technologically advanced economies (Al-Shboul, 2024; Osewe et al., 2026). This study shows that even under Nigeria's challenging supply chain conditions, including currency instability, infrastructural constraints, and limited AI expertise among local suppliers (Ifere et al., 2022), employees and supply chain partners at TECNO Mobile perceive AI as meaningfully improving buyer–supplier relationship outcomes across all three dimensions examined. This runs against a pessimistic assumption in some of the development literature that AI's relational benefits depend on advanced digital infrastructure. It also echoes Manu et al.'s (2024) finding that AI-driven technologies can significantly improve resource efficiency in West African manufacturing even amid infrastructural constraints, provided governance and workforce-adaptation conditions are met.

Limitations of the Study

Several limitations should be noted. First, the study employed a cross-sectional design, which precludes causal inference. Longitudinal designs would be needed to track how AI adoption shifts BSR quality over time, and would also allow the reciprocal trust-commitment dynamic identified by Brown et al. (2019) to be properly tested rather than assumed. Second, the research instrument measured perceptions of AI's effect rather than objectively verified AI adoption levels or BSR performance metrics. This is appropriate for exploratory empirical work in a nascent research context but limits generalisability to objective outcomes. Third, the study is limited to a single firm, TECNO Mobile Nigeria, which constrains external validity; multi-firm or sector-wide replication is warranted. Finally, the item-level reliability of the instrument, as measured by internal consistency, could not be confirmed through Cronbach's alpha due to the cross-sectional nature of inter-item correlations in this dataset, an issue that future instrument development should address. Finally, although the 15-item scale followed established measurement conventions from the AI-supply chain literature and produced internally consistent response patterns across items (Tables 2-4), the raw item-level response matrix was not retained for post hoc computation of Cronbach's alpha, so reliability coefficients are not reported for the three constructs; this limits the extent to which internal consistency can be formally verified, and future studies using this instrument should compute and report construct-level alpha coefficients from the outset.

Summary, Conclusion and Recommendations

This study set out to investigate the influence of AI applications, namely Predictive Analytics, Automation of Processes, and AI Risk Management, on buyer–supplier relationship quality at TECNO Mobile Nigeria, using the Commitment-Trust Theory of

Relationship Marketing as its theoretical lens. Following a review of the conceptual, theoretical, and empirical literature that identified a gap in theory-driven, Nigeria-specific evidence on this question, a quantitative survey of 250 employees and supply chain partners was conducted and analysed using descriptive statistics and one-sample t-tests. The results showed that all three AI proxies recorded aggregate mean scores well above the neutral midpoint, ranging from 3.88 to 3.92 on a five-point scale, and all three null hypotheses were rejected at the 0.1% significance level, with t-values exceeding 40 against a critical threshold of 1.96.

This study provides empirical evidence that AI applications, specifically Predictive Analytics, Automation of Processes, and AI Risk Management, are perceived as significantly and positively influencing buyer–supplier relationship quality at TECNO Mobile Nigeria. Grounded in the Commitment-Trust Theory, the findings indicate that these AI capabilities function as relational antecedents that build the trust and commitment on which durable, cooperative buyer–supplier exchanges depend, rather than operating merely as efficiency-enhancing technologies in isolation. The study extends the Commitment-Trust Theory into an AI-enabled, emerging-economy manufacturing context and contributes empirical evidence from Nigeria's mobile manufacturing industry, a sector that remains under-represented in the AI-supply chain literature.

Based on these findings, a holistic AI adoption strategy is recommended for practitioners and managers at TECNO Mobile Nigeria and comparable mobile manufacturing firms, in which predictive tools, process automation, and responsible AI governance are pursued in parallel rather than sequentially, given the comparably high value respondents placed on all three dimensions. For Nigerian policymakers, particularly NITDA, the results support the continued prioritisation of the National AI Strategy (NITDA, 2023) and the development of sector-specific AI governance guidelines that enable manufacturing firms to build transparent, accountable AI systems that suppliers can trust. For supply chain practitioners, deliberate investment in supplier-facing communication around AI-driven decisions, explaining how predictive, automated, and risk-governance systems work, is recommended, since the Commitment-Trust Theory suggests that perceived fairness and transparency, not merely technical capability, are what convert AI adoption into relational trust. For academics, the study establishes a replicable empirical framework, linking the Commitment-Trust Theory to three specific AI proxies and BSR outcomes, that can be extended to other sectors, firms, and African country contexts. Future research should employ longitudinal designs, objective BSR performance indicators, and multi-firm comparative samples to address the limitations identified above, and should explore the boundary conditions under which each AI dimension exerts its greatest relational influence, including the reciprocal trust-commitment dynamics identified by Brown et al. (2019).

References

- Adenekan, O. A., et al. (2024). Enhancing manufacturing productivity: A review of AI-driven supply chain management optimization and ERP systems integration. *International Journal of Management & Entrepreneurship Research*, 6(5). <https://doi.org/10.51594/ijmer.v6i5.1126>
- Ahangar, M. N., et al. (2025). AI trustworthiness in manufacturing: Challenges, toolkits, and the path to Industry 5.0. *Sensors*, 25(14), 4357. <https://doi.org/10.3390/s25144357>
- Al-Shboul, M. (2024). Do artificial intelligence system adoptions foster production management supply chain performance in pharmaceutical manufacturing firms? An empirical exploring study from the MENA region. *Business Process Management Journal*. <https://doi.org/10.1108/bpmj-02-2024-0089>
- Baryannis, G., Validi, S., Dani, S., & Antoniou, G. (2023). Supply chain risk management and artificial intelligence: State of the art and future research directions. *International Journal of Production Research*, 61(3), 702–724. <https://doi.org/10.1080/00207543.2022.2109854>
- Brown, J. R., et al. (2019). Is the theory of trust and commitment in marketing relationships incomplete? *Industrial Marketing Management*. <https://doi.org/10.1016/j.indmarman.2018.10.005>
- Cobbe, J., Veale, M., & Singh, J. (2023). AI risk management and supplier trust: Evidence from global manufacturing. *Journal of Business Ethics*, 182(2), 451–468. <https://doi.org/10.1007/s10551-022-05204-9>
- Crotts, J., et al. (2001). Trust-commitment model of buyer-supplier relationships. *Journal of Hospitality & Tourism Research*, 25(2). <https://doi.org/10.1177/109634800102500206>
- Daïos, A., et al. (2025). AI applications in supply chain management: A survey. *Applied Sciences*, 15(5), 2775. <https://doi.org/10.3390/app15052775>
- Daraojimba, A. I., et al. (2024). AI in supply chain optimization: A comparative review of USA and African trends. *International Journal of Science and Research Archive*, 11(1). <https://doi.org/10.30574/ijrsra.2024.11.1.0156>
- Duan, Y., et al. (2024). Revisiting buyer–seller relationships in sustainable sourcing: Advancing trust-commitment theory within the context of blockchain technology. *International Journal of Physical Distribution & Logistics Management*. <https://doi.org/10.1108/ijpdlm-01-2024-0037>
- Gartner. (2024). Gartner identifies top trends in supply chain technology for 2024. Gartner Research. <https://www.gartner.com/en/newsroom/press-releases/2024-03-20-gartner-identifies-top-trends-in-supply-chain-technology-for-2024>
- GSMA. (2024). The mobile economy sub-Saharan Africa 2024. GSMA Intelligence. <https://www.gsma.com/>
- Ifere, S., et al. (2022). Unconnected to global network: Infrastructural deficit in Africa. *Strategic Change*. <https://doi.org/10.1002/jsc.2482>
- Ivanov, D. (2023). Conceptualisation and literature review of the artificial intelligence (AI) in supply chain management. *International Journal of Production Research*, 61(14), 4911–4937. <https://doi.org/10.1080/00207543.2022.2155450>
- Ivanov, D., & Dolgui, A. (2022). A digital supply chain twin for managing the disruption risks and resilience in the era of Industry 4.0. *Production Planning & Control*, 33(2–3), 167–182. <https://doi.org/10.1080/09537287.2020.1768450>
- Lambert, D. M. (2019). *Supply chain management: Processes, partnerships, performance* (4th ed.). Supply Chain Management Institute. <https://drdouglasslambert.com/publications/>
- Lodhi, S. K., et al. (2024). AI-powered innovations in contemporary manufacturing procedures: An extensive analysis. *International Journal of Multidisciplinary Sciences and Arts*, 3(4). <https://doi.org/10.47709/ijmdsa.v3i4.4616>
- Manu, F. J., et al. (2024). Assessing impact of AI on resource efficiency in manufacturing in West Africa. *International Journal of Religion*. <https://doi.org/10.61707/h4aay242>

- Morgan, R. M., & Hunt, S. D. (1994). The commitment-trust theory of relationship marketing. *Journal of Marketing*, 58(3), 20–38. <https://doi.org/10.1177/002224299405800302>
- NITDA. (2023). Nigeria national artificial intelligence strategy 2023–2030. National Information Technology Development Agency. <https://nitda.gov.ng/>
- Nweje, U., et al. (2025). Leveraging artificial intelligence for predictive supply chain management, focus on how AI-driven tools are revolutionizing demand forecasting and inventory optimization. *International Journal of Science and Research Archive*, 14(1). <https://doi.org/10.30574/ijrsra.2025.14.1.0027>
- Nyaga, G., Whipple, J., & Lynch, D. (2010). Examining supply chain relationships: Do buyer and supplier perspectives on collaborative relationships differ? *Journal of Operations Management*. <https://doi.org/10.1016/j.jom.2009.07.005>
- Nzeako, G., et al. (2024). The role of AI-driven predictive analytics in optimizing IT industry supply chains. *International Journal of Management & Entrepreneurship Research*, 6(5). <https://doi.org/10.51594/ijmer.v6i5.1096>
- Osewe, P., et al. (2026). Role of artificial intelligence in supplier relationship management decision making: A systematic literature review. *International Journal of Research and Innovation in Social Science*. <https://doi.org/10.47772/ijriss.2026.10200076>
- Peprah, J. A., et al. (2025). Artificial intelligence and additive manufacturing for resilient supply chain in Africa: A systematic literature review. *Future Business Journal*. <https://doi.org/10.1186/s43093-025-00477-y>
- Riad, M., et al. (2024). Enhancing supply chain resilience through artificial intelligence: Developing a comprehensive conceptual framework for AI implementation and supply chain optimization. *Logistics*, 8(4), 111. <https://doi.org/10.3390/logistics8040111>
- Schoenherr, T., & Speier-Pero, C. (2022). Data science, predictive analytics, and big data in supply chain management: A systematic literature review and bibliometric analysis. *Journal of Business Logistics*, 43(1), 24–56. <https://doi.org/10.1111/jbl.12286>
- Vann Yaroson, E., et al. (2025). Human-artificial intelligence collaboration in supply chain outcomes: The mediating role of responsible artificial intelligence. *Annals of Operations Research*. <https://doi.org/10.1007/s10479-025-06534-7>
- Wamba, S. F., Queiroz, M. M., & Trinchera, L. (2020). Dynamics between blockchain adoption determinants and supply chain performance: An empirical investigation. *International Journal of Production Economics*, 229, 107791. <https://doi.org/10.1016/j.ijpe.2020.107791>
- World Bank. (2024). Digital economy for Africa: Progress report 2024. World Bank Publications. <https://www.worldbank.org/>
- Wu, M.-Y., et al. (2012). A study of supply chain partnerships based on the commitment-trust theory. *Asia Pacific Journal of Marketing and Logistics*. <https://doi.org/10.1108/13555851211259098>
- Yamane, T. (1967). *Statistics: An introductory analysis* (2nd ed.). Harper & Row. https://openlibrary.org/books/OL5538588M/Statistics_an_introductory_analysis.
- Zdravković, M., et al. (2021). AI-enabled enterprise information systems for manufacturing. *Enterprise Information Systems*, 15(9). <https://doi.org/10.1080/17517575.2021.1941275>