

ARTIFICIAL INTELLIGENCE ADOPTION IN NIGERIAN PUBLIC PROCUREMENT: A TAM- INSTITUTIONAL THEORY PERSPECTIVE

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Abstract

Artificial intelligence (AI) holds significant promise for transforming public procurement in developing countries by addressing systemic inefficiencies, reducing corruption risks, and improving transparency. However, empirical evidence on the antecedents of AI adoption among procurement officials in Sub-Saharan Africa remains limited, leaving policymakers without the evidence base needed to guide digital procurement reform. This study investigates the determinants of AI adoption intention among public procurement officials in Nigerian federal Ministries, Departments, and Agencies (MDAs), examining the moderating role of institutional pressure on the relationships between individual cognitive predictors and adoption intent. A quantitative cross-sectional survey was administered to 229 purposively sampled procurement officers, Heads of Procurement Units, internal auditors, and project and programme managers across five federal MDAs. Data were analysed using Partial Least Squares Structural Equation Modelling (PLS-SEM) via SmartPLS 4.0. Results reveal that perceived usefulness was the strongest predictor of AI adoption intention ($\beta = 0.429$, $p < 0.001$), followed by perceived ease of use ($\beta = 0.245$, $p < 0.001$). Perceived ease of use also positively predicted perceived usefulness ($\beta = 0.415$, $p < 0.001$), confirming the internal TAM pathway. Institutional pressure partially moderated the findings: it amplified the usefulness–intention relationship ($\beta = 0.112$, $p = 0.039$) but did not moderate the ease-of-use–intention path ($p = 0.562$). The study concludes that AI adoption in Nigerian public procurement is driven primarily by individual utility assessments, selectively conditioned by institutional context. It is recommended that procurement reform initiatives prioritise value demonstration over regulatory mandates, invest in participatory system design to reduce ease-of-use barriers, and equip practitioners with structured AI literacy training.

Keywords: Artificial intelligence, public procurement, Technology Acceptance Model, Institutional Theory, public sector, Digital governance

Introduction

The integration of artificial intelligence (AI) technologies into public sector operations represents one of the most consequential governance transformations of the twenty-first century. Across the globe, governments are increasingly deploying AI-powered tools including machine learning algorithms, natural language processing systems, and automated decision-support platforms to streamline administrative processes, reduce corruption risks, and enhance the quality of public service delivery (Wirtz et al., 2019; Mikhaylov et al., 2018). Within this broader wave of digital transformation, public procurement has emerged as a particularly high-stakes domain for AI adoption, given its direct implications for fiscal efficiency, transparency, and the equitable allocation of public resources (Mergel et al., 2019). As governments worldwide collectively spend an estimated 13% of GDP on public procurement annually (OECD, 2021), the potential of AI to transform tendering, supplier evaluation, and contract monitoring processes carries profound implications for public financial management and governance quality.

Within developing country contexts, however, the adoption of AI in public procurement intersects with a unique constellation of institutional, infrastructural, and human capital challenges that render the dynamics of technology uptake markedly different from those observed in high-income settings. In Nigeria, a federal republic of over 200 million citizens, public procurement has long been characterized by systemic inefficiencies, opacity in contract awards, and susceptibility to corruption challenges that have prompted successive reforms, including the establishment of the Bureau of Public Procurement (BPP) and the enactment of the Public Procurement Act (2007) (Nnawulezi & Kabano, 2025). More recently, the Nigerian government has signalled its commitment to digitizing procurement processes through the National e-Government Masterplan and the Federal Government's broader digital economy agenda (NITDA, 2020). Despite these policy commitments, however, the deployment of AI-based tools in Nigerian public procurement agencies remains nascent and poorly understood, leaving procurement officers, policymakers, and oversight bodies without empirically grounded guidance on the adoption drivers and barriers specific to this context.

To theorize this phenomenon, the present study draws on two complementary theoretical frameworks. The Technology Acceptance Model (TAM), originally proposed by Davis (1989), offers a well-validated account of how individuals' perceptions of a technology's usefulness and ease of use shape their intention to adopt it. TAM has been extensively applied in public sector ICT adoption research (Weerakkody et al., 2013; Shareef et al., 2011), providing a robust baseline for understanding the cognitive antecedents of AI uptake among procurement officials. Recognizing, however, that individual-level cognitive factors alone do not capture the organizational and institutional pressures shaping adoption in bureaucratic settings, this study additionally draws on Institutional Theory (DiMaggio and Powell, 1983), which posits that organizational behaviour is shaped by mimetic, normative, and coercive pressures emanating from the institutional environment. Together, these frameworks provide a richer, multi-level account of AI adoption in public procurement than either theory could furnish alone.

Despite the growing body of literature on AI in government (Wirtz and Müller, 2019; Sun and Medaglia, 2019; Gosh et al., 2025) and on digital adoption in Nigerian public sector organizations (Abdulkareem and Ramli, 2021; Oni et al., 2016), significant empirical gaps persist. Existing studies on AI adoption in procurement have predominantly been conducted in Western and East Asian settings, where institutional maturity, digital infrastructure, and organizational capacity present a fundamentally different adoption landscape (Glas and Kleemann, 2016; Torti, et al., 2025; Yanuarisa et al., 2025). The developing country context marked by infrastructural deficits, limited AI literacy among public servants, weak enforcement of procurement regulations, and the coexistence of formal and informal institutional pressures has received comparatively little systematic scholarly attention. Moreover, extant studies have seldom examined how procurement-specific factors interact with general TAM predictors to shape adoption intentions in this domain.

Against this backdrop, the present study addresses the following research questions: (i) What is the influence of perceived usefulness and perceived ease of use on the intention of Nigerian procurement officials to adopt AI tools? (ii) How does institutional pressure moderate the relationship between individual-level TAM predictors and AI adoption intention? (iii) What contextual factors specific to the Nigerian public procurement environment shape AI adoption readiness? In addressing these questions, this study makes three contributions. First, it extends the application of TAM to AI adoption in public procurement in a developing country context. Second, it integrates Institutional Theory with TAM in a moderation framework, providing a multi-level theoretical account of how cognitive and structural factors jointly determine adoption behaviour. Third, it generates actionable insights for policymakers and procurement reform advocates in Nigeria and comparable Sub-Saharan African contexts.

Literature Review

Artificial Intelligence

Artificial intelligence (AI) refers to the capacity of computational systems to perform tasks that ordinarily require human cognitive abilities, including reasoning, learning, pattern recognition, and autonomous decision-making (Russell and Norvig, 2020). Within the public administration literature, AI is distinguished from earlier waves of e-government on the basis of its capacity for predictive analytics, adaptive learning, and autonomous decision support, rather than mere digitization of existing administrative processes (Wirtz et al., 2019; Dwivedi et al., 2021). AI systems in organizational contexts typically take the form of machine learning algorithms, natural language processing tools, robotic process automation, and intelligent decision-support platforms that operate with varying degrees of human oversight. The deployment of such systems in government settings has accelerated markedly in recent years, as public sector organizations seek technological solutions to longstanding challenges of efficiency, accountability, and service quality (Ghosh et al., 2025; Andhov et al., 2025). Notwithstanding this momentum, AI adoption in government remains uneven, with developing country contexts facing distinct barriers rooted in infrastructural constraints, limited digital literacy, and institutional capacity gaps that are seldom adequately addressed in frameworks developed from Western or East Asian experience (Panda et al., 2025).

Public Procurement

Public procurement refers to the process through which government entities acquire goods, services, and works from external suppliers on behalf of the state (Thai, 2001). As a function that governs a substantial share of public expenditure estimated at approximately 13% of GDP in most economies (OECD, 2021) — procurement is simultaneously a site of significant fiscal exposure, a regulatory compliance domain, and a governance institution with direct implications for market fairness, anti-corruption, and development outcomes (Nnawulezi and Kabano, 2025). The systemic vulnerabilities of manual procurement processes — including susceptibility to bid rigging, conflict of interest in supplier selection, delays in contract execution, and opacity in award decisions — are well documented in both developed and developing country contexts (Glas and Kleemann, 2016; Allen et al., 2025). In Nigeria specifically, procurement governance has been a persistent reform priority since the enactment of the Public Procurement Act (2007) and the establishment of the Bureau of Public Procurement (BPP), yet implementation challenges rooted in weak enforcement, institutional fragility, and governance culture have continued to constrain procurement effectiveness (Nnawulezi and Kabano, 2025). These challenges create both the imperative and the opportunity for technological intervention in the procurement function.

Artificial Intelligence in Public Procurement

Artificial intelligence, broadly defined as the capacity of computational systems to perform tasks that ordinarily require human cognitive abilities including reasoning, learning, pattern recognition, and decision-making has emerged as one of the most transformative technological forces reshaping contemporary governance (Andhov, et al., 2025). Within the public administration literature, AI is increasingly distinguished from earlier waves of e-government on the basis of its capacity for autonomous

decision support, predictive analytics, and adaptive learning, rather than mere digitization of existing processes (Wirtz et al., 2019; Dwivedi et al., 2021). For the purposes of this study, AI adoption in public procurement refers to the acceptance and use of AI-powered tools including algorithmic supplier evaluation systems, automated tender analysis platforms, anomaly detection tools for fraud prevention, and predictive contract monitoring software by procurement officers in the discharge of their institutional responsibilities.

Public procurement represents a particularly consequential arena for AI deployment. As a function that governs the acquisition of goods, services, and works on behalf of the state, procurement is simultaneously a site of significant fiscal exposure, a regulatory compliance domain, and a governance institution with direct implications for market fairness and anti-corruption (Thai, 2001; Pand et al., 2025). The systemic vulnerabilities of manual procurement including susceptibility to bid rigging, conflict of interest in supplier selection, and delays in contract execution are precisely the inefficiencies that AI applications are designed to address (Glas & Kleemann, 2016; Allen et al., 2025). Empirical evidence from early AI deployments in procurement contexts is encouraging: studies from South Korea and the European Union have documented reductions in procurement cycle times, improvements in supplier shortlisting accuracy, and enhanced anomaly detection in contract pricing when AI tools are integrated into procurement workflows (Allen et al., 2025).

In developing country contexts, however, the evidence base is substantially thinner and the adoption landscape markedly more complex. Procurement systems in Sub-Saharan Africa, including Nigeria, have historically been characterized by institutional fragility, limited digital infrastructure, and governance cultures in which informal norms may operate alongside or in tension with formal procurement regulations (Nnawulezi & Kabano, 2025). Nigeria's Bureau of Public Procurement (BPP), established under the Public Procurement Act of 2007, has made progress in standardizing processes and introducing e-procurement elements such as the National Public Procurement Portal; however, AI integration beyond basic digitization remains exploratory and largely unevaluated (NITDA, 2020).

AI Adoption Intention

Adoption intention, defined as an individual's subjective probability that they will use a particular technology in the future (Davis et al., 1989), represents the most widely employed dependent variable in the technology acceptance literature and serves as the closest behavioural proxy for actual technology use in survey-based research designs. The primacy of intention as a predictor of behaviour is well established in the social psychology tradition, rooted in the Theory of Reasoned Action (Ajzen & Fishbein, 1980) and subsequently incorporated into virtually all major technology adoption models, including TAM, UTAUT, and the Innovation Diffusion Theory (Rogers, 2003). In the context of AI specifically, adoption intention captures procurement officials' readiness to integrate AI tools into their decision-making workflows – an attitudinal precursor to the behavioural changes that ultimately determine whether AI investments translate into governance improvements.

The literature on AI adoption intention in organizational settings has grown substantially in recent years, though it remains concentrated in private sector and healthcare contexts (Mikalef et al., 2022; Choudhury et al., 2020; Sharma et al., 2025). Studies consistently identify perceived usefulness and perceived competence as among the strongest predictors of AI adoption intention across domains (Gursoy et al., 2019; Pillai and Sivathanu, 2020; Wang et al., 2025). In public sector settings specifically, additional factors such as risk aversion, accountability concerns, and the perceived legitimacy of algorithmic decision-making introduce complexity absent from private sector models (Algan et al., 2019; Badda, 2025).

Perceived Usefulness and Perceived Ease of Use

Perceived Usefulness

Perceived usefulness (PU), one of the two core constructs of the Technology Acceptance Model, refers to the degree to which an individual believes that using a particular technology will enhance their job performance (Davis, 1989). Across more than three decades of empirical investigation, PU has consistently

emerged as the strongest predictor of technology adoption intention and actual use, demonstrating robust effects across industries, cultures, and technology types (King and He, 2006; Venkatesh and Bala, 2008). In the context of AI tools in public procurement, PU manifests as procurement officers' belief that AI applications will improve the quality and efficiency of their tendering, evaluation, and contract monitoring activities. Empirical support for the PU–adoption intention relationship is well established: Shareef et al. (2011) documented strong PU effects on e-government adoption intention among civil servants in developing countries, while Alrawabdeh (2022) confirmed PU as the dominant predictor of e-procurement adoption intention in Jordan ($\beta = 0.41$). Sun et al. (2023), in a meta-analysis of 67 AI adoption studies, confirmed PU as the most robust predictor of AI adoption intention ($r = 0.52$).

H1: Perceived usefulness will positively predict AI adoption intention among Nigerian public procurement officials.

Perceived Ease of Use

Perceived ease of use (PEOU) refers to the degree to which an individual believes that using a technology will be free of cognitive and physical effort (Davis, 1989). Within the TAM framework, PEOU exerts both a direct effect on adoption intention and an indirect effect mediated through PU: a system perceived as easy to use is also likely to be perceived as more useful, because effort savings are themselves a dimension of productivity (Venkatesh and Davis, 2000). In the Nigerian public sector, where digital literacy remains heterogeneous and access to technical support is limited, the cognitive demands of new technology systems loom particularly large as adoption barriers (Oni et al., 2016; Abdulkareem & Ramli, 2021). Oni et al. (2016) found ease of use a significant predictor of e-government adoption among Nigerian civil servants, while Choudhury et al. (2020) demonstrated that PEOU remained a significant direct predictor of AI adoption intention among healthcare professionals even after controlling for usefulness.

H2: Perceived ease of use will positively predict AI adoption intention among Nigerian public procurement officials.

H3: Perceived ease of use will positively predict perceived usefulness of AI tools among Nigerian public procurement officials.

Institutional Pressure

Institutional Theory, as developed by DiMaggio and Powell (1983), posits that organizations do not make adoption decisions purely on the basis of technical rationality or individual utility. Rather, they operate within institutional environments that generate expectations about legitimate and appropriate behaviour expectations to which organizations conform in order to secure social acceptance, resources, and legitimacy (Scott, 2001). The collective force of these environmental expectations is captured in the construct of institutional pressure, which encompasses regulatory mandates, peer organization behaviour, and professional norms that together define what constitutes acceptable practice within an organizational field (DiMaggio and Powell, 1983; Teo et al., 2003).

In public sector technology adoption, institutional pressure has proven a significant explanatory variable beyond what individual-level cognitive models capture alone. Liang et al. (2007) demonstrated that institutional pressure significantly predicted enterprise system adoption in organizations, complementing and at times amplifying the effects of perceived utility. Oliveira and Martins (2011) similarly found institutional forces to be among the strongest predictors of technology adoption in regulated organizational environments. In the Nigerian federal civil service, institutional pressure operates through a convergent set of forces: top-down policy directives from the BPP and NITDA; the observed uptake of AI tools by comparator ministries and international procurement agencies; and the growing professional endorsement of data analytics competencies through capacity-building programmes supported by the World Bank and the African Development Bank (NITDA, 2020; Abdulkareem et al., 2022).

H4: Institutional pressure will positively moderate the relationship between TAM predictors (perceived usefulness and perceived ease of use) and AI adoption intention.

Theoretical Framework

This study integrates the Technology Acceptance Model (Davis, 1989) and Institutional Theory (DiMaggio and Powell, 1983) into a unified conceptual model of AI adoption intention in Nigerian public procurement. The two frameworks operate at complementary levels of analysis – TAM at the individual cognitive level, Institutional Theory at the organizational and environmental level and are connected through a moderation logic: PU and PEOU constitute the primary psychological drivers of adoption intention, while institutional pressure shapes the strength of these relationships by altering the incentive structures and normative contexts within which individual perceptions are formed and acted upon. By introducing institutional pressure as a moderator of the TAM pathways, the present model (Figure 1) captures the conditions under which cognitive predictors are more or less influential, generating theoretically richer insights than either framework could provide alone (Bagozzi, 2007; Williams et al., 2009).

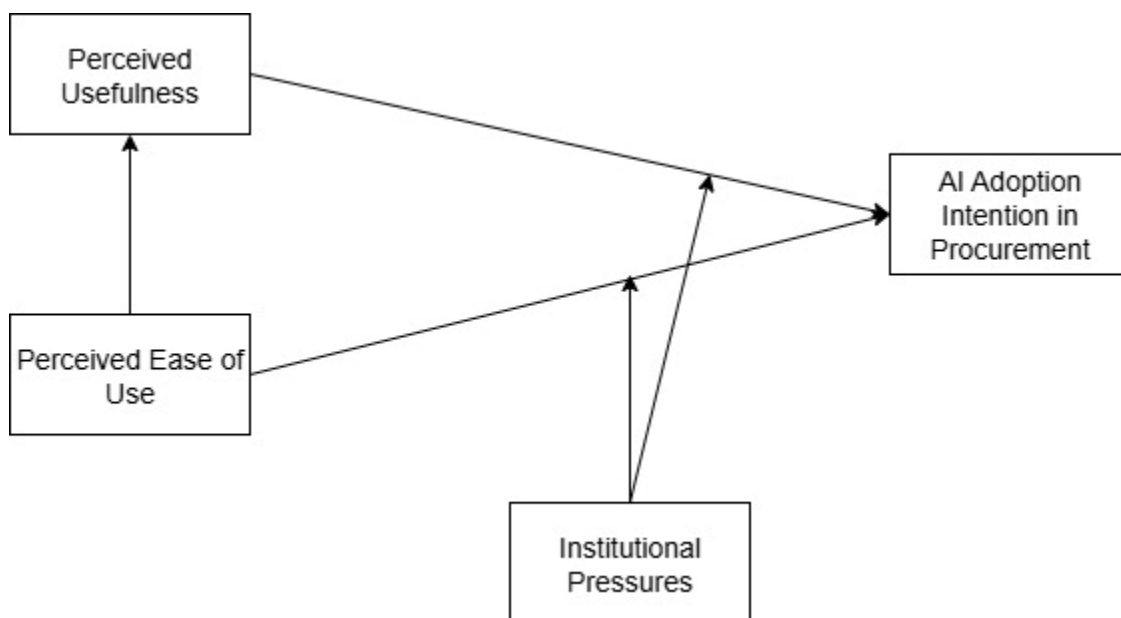


Figure 1: Conceptual Model

Source: Authors' conceptualization

Methodology

This study adopted a quantitative cross-sectional survey design to test the hypothesized relationships among perceived usefulness, perceived ease of use, institutional pressure, and AI adoption intention in the Nigerian federal public procurement context. The target population comprised procurement officers, Heads of Procurement Units (HoPUs), internal auditors, and project and programme managers employed across five federal Ministries, Departments, and Agencies (MDAs) selected on the basis of their high procurement volumes and active capital project involvement. A purposive sampling strategy was employed to ensure role-relevance among all respondents. Of 280 questionnaires distributed proportionally across the five MDAs, 243 were returned (86.8% response rate), and 229 were retained as usable after screening for completeness. All constructs were measured using reflective multi-item scales adapted from validated instruments Davis (1989) for perceived usefulness and ease of use, Liang et al. (2007) and Teo et al. (2003) for institutional pressure, and Davis et al. (1989) and Venkatesh and Davis (2000) for adoption intention

— rated on a five-point Likert scale and pilot-tested with 15 procurement practitioners following Brislin's (1986) adaptation guidelines. Data were analysed using Partial Least Squares Structural Equation Modelling (PLS-SEM) in SmartPLS 4.0, following Anderson and Gerbing's (1988) two-stage procedure for measurement and structural model assessment. Common method bias was addressed using Harman's single factor test (23.7%) and full collinearity assessment (all VIF values < 3.3), both confirming the absence of substantive bias.

Results

Respondent Profile and Descriptive Statistics

Out of the 229 usable responses, male respondents constituted 61.1% of the sample. The dominant age bracket was 31–40 years (44.5%), followed by 41–50 years (31.4%), under 30 years (14.4%), and above 50 years (9.6%). In terms of educational attainment, 52.4% held a first degree, 33.6% held a postgraduate qualification, and 14.0% held a professional certification. Procurement officers constituted the largest group (38.4%), followed by project and programme managers (24.5%), internal auditors (21.0%), and HoPUs (16.2%). The majority reported six to fifteen years of public sector service (49.3%).

Table 1 presents the means, standard deviations, and inter-construct correlations for all study variables. Construct means ranged from 3.468 to 3.493, with standard deviations of 0.702–0.715. Perceived Usefulness demonstrated the strongest bivariate correlation with AI Adoption Intention ($r = 0.531$), followed by Perceived Ease of Use ($r = 0.423$) and Institutional Pressure ($r = 0.201$). All correlations were in the theoretically anticipated directions.

Table 1: Descriptive Statistics and Inter-Construct Correlations

Construct	Mean	SD	1	2	3	4
1. Perceived Usefulness (PU)	3.384	0.712				
2. Perceived Ease of Use (PEOU)	3.421	0.702	0.415			
3. Institutional Pressure (IP)	3.493	0.715	0.042	-0.100		
4. AI Adoption Intention (INT)	3.568	0.705	0.531	0.423	0.201	

Note: N = 229. Correlations $\geq |0.13|$ are significant at $p < .05$ (two-tailed).

Measurement Model Assessment

Prior to evaluating the structural model, the measurement model was assessed for indicator reliability, internal consistency, convergent validity, and discriminant validity (Anderson and Gerbing, 1988). All item loadings exceeded 0.70 (Hair et al., 2019). Cronbach's alpha values ranged from 0.824 to 0.931, and composite reliability (CR) values from 0.905 to 0.938, all exceeding the 0.70 threshold. AVE values ranged from 0.625 to 0.704, surpassing the 0.50 convergent validity threshold (Fornell and Larcker, 1981). Discriminant validity was confirmed via HTMT ratios (Henseler et al., 2015), with all values falling below 0.85 (range: 0.076–0.613). Tables 2 and 3 present the measurement model and HTMT results respectively.

Table 2: Measurement Model Results

Construct	Item	Item Description	Loading	α	CR	AVE
Perceived Usefulness (PU)	PU1	Using AI tools would improve my overall effectiveness in procurement tasks.	0.803	0.909	0.926	0.677

	PU2	AI tools would enhance my ability to evaluate suppliers accurately.	0.841			
	PU3	Using AI tools would increase my productivity in processing procurement requests.	0.819			
	PU4	AI tools would improve the quality of my procurement decisions.	0.827			
	PU5	Using AI tools would make it easier to detect irregularities in procurement processes.	0.815			
	PU6	AI tools would make it easier for me to identify the best-value supplier.	0.832			
Perceived Ease of Use (PEOU)	PEOU1	I would find AI procurement tools easy to use.	0.812	0.896	0.923	0.667
	PEOU2	Learning to use AI tools for procurement would be easy for me.	0.834			
	PEOU3	My interaction with AI procurement systems would be clear and understandable.	0.798			
	PEOU4	I would find it easy to learn how to use AI tools in my procurement work.	0.821			
	PEOU5	Interacting with AI procurement systems would not require a great deal of mental effort.	0.809			
	PEOU6	I would find it easy to get AI tools to do what I want in my procurement tasks.	0.826			
Institutional Pressure (IP)	IP1	Government policies and directives encourage the adoption of AI in public procurement.	0.774	0.931	0.938	0.625
	IP2	The federal government has issued guidelines that support AI adoption in procurement.	0.791			
	IP3	There are regulatory requirements that make it necessary to adopt AI tools in procurement.	0.813			
	IP4	Other federal agencies similar to mine are adopting AI tools for their procurement processes.	0.768			
	IP5	Many organizations in my sector have adopted AI tools for their procurement operations.	0.802			

	IP6	My agency would adopt AI tools in order to keep pace with comparable federal MDAs.	0.795			
	IP7	Professional associations in procurement advocate for the use of AI-based tools.	0.788			
	IP8	Procurement training and capacity-building programmes encourage the adoption of AI tools.	0.776			
	IP9	Experts and professional networks in my field endorse the use of AI in procurement processes.	0.809			
AI Adoption Intention (INT)	INT1	I intend to use AI tools to support my procurement responsibilities in the next twelve months.	0.836	0.824	0.905	0.704
	INT2	I plan to adopt AI tools for procurement tasks whenever they become available in my agency.	0.851			
	INT3	I would recommend AI tools to colleagues involved in procurement activities.	0.842			
	INT4	I expect to use AI tools regularly in my procurement work in the near future.	0.828			

Note: α = Cronbach's Alpha; CR = Composite Reliability; AVE = Average Variance Extracted.

Table 3: HTMT Discriminant Validity Ratios

	PU	PEOU	IP	INT
Perceived Usefulness (PU)				
Perceived Ease of Use (PEOU)	0.459			
Institutional Pressure (IP)	0.076	0.123		
AI Adoption Intention (INT)	0.613	0.494	0.228	

Note: All values below the 0.85 threshold confirm discriminant validity (Henseler et al., 2015).

Common Method Bias Assessment

Harman's single factor test yielded a single-factor variance of 23.7%, well below the 50% threshold (Podsakoff et al., 2003). Full collinearity assessment confirmed VIF values of 1.218 (PU), 1.228 (PEOU), and 1.019 (IP), all below the 3.3 criterion (Kock, 2015). Taken together, these results indicated that common method bias did not constitute a substantive threat to the validity of the findings.

Structural Model and Hypothesis Testing

The structural model was evaluated using PLS-SEM with 5,000 bootstrap resamples. Table 4 presents the full hypothesis testing results. The model explained 17.2% of the variance in Perceived Usefulness ($R^2 =$

0.172) and 33.2% of the variance in AI Adoption Intention at the main effects stage ($R^2 = 0.332$), rising to 39.3% upon inclusion of moderation terms ($R^2 = 0.393$).

H1 was strongly supported: Perceived Usefulness significantly and positively predicted AI Adoption Intention ($\beta = 0.429$, $t = 7.188$, $p < 0.001$, $f^2 = 0.229$), emerging as the most influential predictor in the model. H2 was also supported: Perceived Ease of Use demonstrated a significant positive direct effect on AI Adoption Intention ($\beta = 0.245$, $t = 4.106$, $p < 0.001$, $f^2 = 0.075$). H3 was confirmed, with Perceived Ease of Use significantly predicting Perceived Usefulness ($\beta = 0.415$, $t = 6.868$, $p < 0.001$, $f^2 = 0.208$).

H4 received partial support. The interaction between Institutional Pressure and Perceived Usefulness on Adoption Intention was statistically significant ($\beta = 0.112$, $t = 2.072$, $p = 0.039$), with the moderation block yielding an incremental R^2 of 0.061 and $f^2 = 0.101$ (medium effect).

Table 4: Structural Model Results and Hypothesis Testing

Hyp.	Path	β	t-value	p-value	f^2	Decision
H1	PU → INT	0.429	7.188	< 0.001	0.229	Supported
H2	PEOU → INT	0.245	4.106	< 0.001	0.075	Supported
H3	PEOU → PU	0.415	6.868	< 0.001	0.208	Supported
H4a	IP × PU → INT	0.112	2.072	0.039	0.101*	Partially Supported
H4b	IP × PEOU → INT	0.034	0.580	0.562		Not Supported

Note: β = standardised path coefficient; t-values based on 5,000 bootstrap resamples; * f^2 reported for H4a + H4b moderation block combined. PU = Perceived Usefulness; PEOU = Perceived Ease of Use; IP = Institutional Pressure; INT = AI Adoption Intention.

Endogenous Variable Explained Variance

Endogenous Construct	R^2 (Main Effects)	R^2 (With Moderation)
Perceived Usefulness (PU)	0.172	
AI Adoption Intention (INT)	0.332	0.393

Discussion of Findings

This study examined the factors shaping AI adoption intention among procurement officials in selected Nigerian federal MDAs, drawing on an integrated framework combining TAM (Davis, 1989) and Institutional Theory (DiMaggio and Powell, 1983). The findings broadly confirmed the TAM pathways in this novel context while revealing a theoretically meaningful asymmetry in how institutional pressure operates as a moderator amplifying the utility–intention relationship but leaving the ease-of-use pathway largely unaffected by environmental forces.

Consistent with H1 and the instrumental rationality logic of TAM, perceived usefulness emerged as the single most powerful predictor of AI adoption intention ($\beta = 0.429$, $f^2 = 0.229$). This finding was in

agreement with Shareef et al. (2011), Alrawabdeh (2022), and the meta-analytic evidence of Sun et al. (2023), confirming the primacy of usefulness across technology adoption contexts. In the Nigerian procurement environment where procurement failures carry significant reputational and legal consequences for individual officers the performance-enhancing potential of AI constitutes a direct response to the professional risk landscape, amplifying a relationship that is already robust in the general adoption literature.

H2 was also supported, with perceived ease of use demonstrating a significant independent direct effect on AI adoption intention ($\beta = 0.245$, $f^2 = 0.075$). This finding was consistent with Choudhury et al. (2020) and Oni et al. (2016). In the Nigerian federal civil service, where digital fluency is unevenly distributed and prior AI exposure limited, anticipated interaction complexity represents a meaningful and distinct psychological barrier. The dual-pathway dynamic observed usefulness shaping whether officials want to adopt, ease of use shaping whether they feel capable of doing so has important implications for AI deployment strategy.

The results confirmed H3, with perceived ease of use significantly predicting perceived usefulness ($\beta = 0.415$, $f^2 = 0.208$), replicating the internal TAM pathway robustly (King and He, 2006). This finding reinforced the importance of addressing ease of use not merely as a direct adoption barrier but as a precondition for the formation of positive usefulness beliefs a sequencing implication directly relevant to the design and introduction of AI procurement systems in the Nigerian context.

H4 was partially supported, yielding a theoretically important asymmetric moderation pattern. The interaction between institutional pressure and perceived usefulness on adoption intention was significant ($\beta = 0.112$, $p = 0.039$), consistent with Liang et al. (2007) and Teo et al. (2003). Simple slope analysis confirmed the amplifying effect: the PU–intention path was nearly twice as strong at high institutional pressure ($\beta = 0.522$) than at low institutional pressure ($\beta = 0.299$). The non-significant IP \times PEOU interaction ($p = 0.562$) was itself theoretically instructive: institutional forces, however strong, could not compensate for the adoption barriers introduced by anticipated interaction difficulty. This distinction that institutional pressure engages motivational but not competency-based pathways has direct implications for procurement AI reform design and would have been obscured had institutional pressure been modelled as a main effect.

The findings carry significant theoretical and practical implications. Theoretically, the study extends TAM's boundary conditions to AI-specific adoption in public procurement within a Sub-Saharan African federal governance context a setting where the model's core propositions had not previously been empirically examined. The robust replication of both direct TAM pathways and the internal PEOU-to-PU relationship, with effect sizes comparable to meta-analytic benchmarks (King and He, 2006; Sun et al., 2023), strengthens confidence in TAM's cross-contextual generalizability. More significantly, the integration of Institutional Theory as a moderating rather than additive framework reveals a theoretically important asymmetry: institutional pressure selectively conditions the motivational pathway linking perceived usefulness to adoption intention but exerts no significant influence on the competency-based ease-of-use pathway. This challenges the implicit assumption in the integrated TAM and Institutional Theory literature that environmental forces uniformly amplify all adoption antecedents, and advances understanding of when and how institutional context shapes technology adoption in bureaucratic settings. The unexplained variance ($R^2 = 0.393$) further points to AI-specific constructs — algorithmic trust, accountability concern, and organisational readiness — as productive extensions for future theoretical work.

Practically, the primacy of perceived usefulness and its amplification under high institutional pressure implies that procurement reform initiatives should prioritise value demonstration over regulatory mandates specifically through pilot deployment evidence, inter-agency benchmarking, and formal institutional endorsements from the BPP and NITDA. For MDA managers and HoPUs, the independent direct effect of ease of use signals that participatory system design involving intended users at the pre-deployment stage is a non-negotiable prerequisite, not an implementation amenity. For capacity-building institutions including

WAIFEM, ASCON, and CIPS Nigeria, the non-significant $IP \times PEOU$ interaction indicates that normative endorsement alone is insufficient structured, hands-on algorithmic literacy training must accompany policy messaging to translate institutional pressure into genuine adoption readiness among procurement practitioners.

6. Conclusion

Summary of Findings

This study set out to examine the determinants of AI adoption intention among procurement officials in selected Nigerian federal MDAs and to investigate the moderating role of institutional pressure. Drawing on TAM and Institutional Theory, data from 229 respondents across five federal MDAs were analysed using PLS-SEM. The findings confirmed perceived usefulness as the strongest predictor of adoption intention, with perceived ease of use contributing an independent direct effect and serving as a cognitive precondition for usefulness perception formation. Institutional pressure partially moderated the TAM relationships: amplifying the usefulness–intention pathway while leaving the ease-of-use–intention pathway unaffected a theoretically important asymmetry that distinguished motivational from competency-based adoption barriers. Taken together, the results underscore the dual-engine nature of AI adoption motivation in public procurement: individual cognitive assessments and institutional environment must both be addressed concurrently for AI to fulfil its transformative governance potential.

Recommendations

Based on the findings of this study, the following recommendations are advanced for policymakers, public sector managers, and capacity-building institutions engaged in AI-driven procurement reform in Nigeria and comparable developing country contexts.

The Bureau of Public Procurement and the National Information Technology Development Agency should develop and disseminate evidence-based communication frameworks that document the measurable performance benefits of AI procurement tools through structured pilot deployments across federal MDAs, rather than relying on regulatory directives alone to drive adoption. Institutional endorsement should accompany, not precede, demonstrated utility.

Heads of Procurement Units and MDA management should institutionalise participatory design processes for all AI procurement system deployments, ensuring that procurement officers, internal auditors, and project managers contribute to interface specification and workflow integration decisions prior to rollout. Ease of use must be engineered into systems before deployment, not addressed reactively after resistance emerges.

Capacity-building institutions including WAIFEM, ASCON, and the CIPS Nigeria chapter should redesign their digital governance curricula to incorporate structured, hands-on modules in AI tool interaction, algorithmic output interpretation, and the ethical governance of AI-assisted procurement decisions. Professional endorsement of AI literacy must be matched by practical training infrastructure capable of converting normative expectations into operational competence among procurement practitioners.

Limitations and Directions for Future Research

This study is not without limitations, each of which simultaneously defines the boundary conditions of the findings and points toward productive directions for future inquiry. The cross-sectional design, while appropriate for this initial investigation, precludes causal inference and cannot rule out reverse causation in the TAM pathways. Future longitudinal studies tracking respondents from initial AI exposure through adoption intention to actual use behaviour would substantially strengthen causal claims and illuminate the temporal dynamics of the observed relationships. The sample drawn exclusively from five federal MDAs

in the Federal Capital Territory restricts generalizability to state and local government procurement systems and to comparable developing country contexts. Comparative studies across Ghana, Kenya, Rwanda, and South Africa representing a range of e-government maturity levels would advance the cross-contextual applicability of the TAM and Institutional Theory integration tested here.

The reliance on self-reported perceptual measures introduces the possibility of social desirability bias, particularly in the institutional pressure items. Future research would benefit from multi-source designs triangulating self-reported intentions with supervisory assessments or behavioural trace data from actual AI procurement platforms. Finally, the composite operationalisation of institutional pressure precluded examination of whether its coercive, mimetic, and normative dimensions exert differential moderating effects on the TAM pathways. Disaggregating these dimensions, and incorporating AI-specific constructs such as algorithmic trust, accountability concern, and perceived organisational readiness, would substantially enrich the explanatory model and generate more targeted policy implications in future studies.

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