

Assessing Critical Success Factors for Implementing Artificial Intelligence (AI) in Public Procurement

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Abstract

Artificial intelligence (AI) offers significant potential to enhance efficiency and accountability in public procurement, yet its implementation remains limited, particularly in developing economies. Drawing on Institutional Theory and the Technology-Organisation-Environment (TOE) framework, this study identifies and clusters critical success factors (CSFs) for AI implementation in Nigerian public procurement. A quantitative survey of 71 procurement professionals across federal Ministries, Departments, and Agencies (MDAs) assessed 38 CSFs derived from literature. Data were analysed using descriptive statistics and exploratory factor analysis (EFA) with principal component extraction and Varimax rotation. Results identified appropriate team skills and knowledge, adequate technical know-how in AI tools, and adequate knowledge of AI applications as the top three CSFs. EFA revealed a ten-component model explaining 76.13% of variance, comprising: internal process coordination, data infrastructure, strategic leadership, vendor partnership, early-stage planning, user competence, data governance, project clarity, executive support, and technical compatibility. All components demonstrated acceptable reliability (Cronbach's $\alpha = .623-.891$). The study contributes an empirically derived ten-factor model to guide evidence-based policymaking for AI adoption in public procurement. Limitations include the exploratory nature of the findings and the Nigeria-specific context, requiring validation in other settings.

Keywords: Artificial intelligence, critical success factors, public procurement, implementation, factor analysis, developing economy

Paper type: Research paper

1. Introduction

Public procurement plays a vital role in how governments deliver goods, works, and services to citizens. Yet, the process is often hindered by inefficiencies, lack of transparency, and outdated manual procedures (Allal-Chérif et al., 2021; Rejeb et al., 2018). Among technological innovations, Artificial Intelligence (AI) stands out as a tool with strong potential to transform procurement practices (Constant et al., 2022; Cui et al., 2022).

Research on digitalisation in procurement suggests that technologies such as AI can bring significant value (Kosmol et al., 2019). AI has proven useful in cost estimation, supplier evaluation, auctions, and risk management (Jahani et al., 2021; Niyazbekova et al., 2021). Similarly, AI shows promise in improving planning, strategy development, and contract management (Buchholz & Grabbe, 2022; Schulze-Horn et al., 2020).

Despite these benefits, AI use in public procurement remains very limited (Andersson, 2025). Unlike private procurement, public procurement is bound by stricter requirements for openness, ethical considerations, and complex regulations (Sanchez-Graells, 2024; Nowicki,

2020). These factors create unique challenges, including data protection concerns, need for high-quality datasets, limited digital skills, and uncertainty about AI applications (Nowicki, 2020; Guida et al., 2023).

Recent studies have examined barriers to AI adoption and developed AI-based decision support systems (Rejeb, 2018; Siciliani et al., 2023; Andersson, 2025). However, there remains a lack of research focused on assessing the Critical Success Factors (CSFs) necessary for successful AI implementation in public procurement.

This study bridges this gap by identifying and categorising the success factors required for AI adoption in public procurement within a developing economy context.

2. Literature Review

2.1. Defining AI in Public Procurement

This study adopts a functional definition of AI in public procurement, encompassing three primary use cases: (a) automated supplier pre-qualification and risk assessment, (b) intelligent contract monitoring and anomaly detection, and (c) predictive analytics for

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demand forecasting and price optimisation. These use cases span multiple stages of the procurement lifecycle, including planning, preparation, contract award, and contract management. Implementation success is defined as the effective integration of these AI capabilities into procurement workflows, resulting in measurable improvements in efficiency, compliance, or cost savings.

2.2. Critical Success Factors

Several studies have contributed to understanding determinants of AI implementation. Wuni (2025) investigated CSFs for AI in construction projects, identifying organisational readiness, data quality and technical competence as fundamental enablers. Makarius et al. (2020) emphasised employee skills, leadership support and organisational culture. Solaimani and Swaak (2023) highlighted

interdependence between strategy, structure and technology readiness. Merhi (2023) focused on AI readiness in public organisations, identifying data management, regulatory alignment and digital competency as core determinants.

The 38 CSFs presented in Table 1 were derived through systematic literature synthesis of these four key studies. Overlapping factors across studies were merged into single items. For example, "top management commitment" (Merhi, 2023) and "leadership commitment" (Wuni, 2025) were combined into "Top management commitment and support" (CSF9).

This study draws on two complementary theoretical lenses to interpret the CSFs. Institutional Theory (DiMaggio & Powell, 1983) explains coercive (regulatory), mimetic (peer adoption), and normative

Table 1: Success factors for implementing AI

Code	Critical Success Factor
CSF1	Clear strategy and business model for AI
CSF2	Managerial competence and capabilities in AI
CSF3	Effective risk management for AI technologies
CSF4	Effective AI leadership and governance
CSF5	Adequate financial resources allocation
CSF6	Conducive organisational culture for AI
CSF7	Sufficient organisational readiness for AI
CSF8	Clear assignment of roles and accountabilities
CSF9	Top management commitment and support
CSF10	Extensive front-end planning for AI
CSF11	Effective change management strategy
CSF12	Clear vision and clarity of business case
CSF13	Alignment of AI with strategy and needs
CSF14	Clear and realistic AI objectives
CSF15	Supportive organisational infrastructure
CSF16	Robust supportive technological infrastructure
CSF17	Appropriate AI techniques and tools
CSF18	Adequate computing capabilities
CSF19	Adequate knowledge of AI applications
CSF20	Adequate technical know-how in AI tools
CSF21	Strong expertise of AI developers
CSF22	Robust integration into workflow
CSF23	Appropriate team skills and knowledge
CSF24	Appropriate integration with legacy systems
CSF25	Appropriate AI algorithms and models
CSF26	Technical compatibility with infrastructure
CSF27	Familiarity with AI tools
CSF28	Support from qualified AI vendors
CSF29	Early client commitment to AI
CSF30	Early involvement of AI consultants
CSF31	Early cross-functional team collaboration
CSF32	High quality and integrity of data
CSF33	Effective data management and governance
CSF34	Cyber security of data and algorithms
CSF35	Availability of high-value data
CSF36	Robust data ecosystems
CSF37	Sufficient quantity and flow of data
CSF38	Adequate data storage and cloud resources

(professional standards) pressures shaping AI adoption. The Technology-Organisation-Environment (TOE) framework (Baker, 2012) provides a multi-level categorisation of factors influencing technology adoption across technological, organisational, and environmental contexts.

3. Methodology

3.1. Questionnaire Design and Administration

A structured questionnaire was developed based on the literature review. To enhance content validity, the questionnaire was reviewed by a senior lecturer with over 10 years of industry and academic experience. The questionnaire comprised two parts: demographic information, and 38 Likert-scale items (1=strongly disagree to 5=strongly agree) measuring CSFs.

Respondents were procurement professionals from Nigerian federal MDAs. Using Yamane's (1967) formula, 109 MDAs were sampled. Of 109 questionnaires distributed, 71 (65%) were retrieved and analysed. Table 2 presents respondent demographics.

retention used eigenvalues >1.0 and scree plot inspection. Factor loading threshold of $|0.5|$ was applied.

The Kaiser-Meyer-Olkin (KMO) measure was .772, exceeding the 0.6 threshold. Bartlett's Test of Sphericity was significant ($\chi^2 = 1880.108$, $df = 703$, $p < .001$), confirming data suitability for EFA.

Regarding sample size, while the 71:38 variable ratio (1.9:1) is below conventional heuristics, simulation studies (de Winter et al., 2009) demonstrate that EFA can yield stable solutions with smaller samples when communalities are high (>0.6) and factor loadings are strong (>0.7). Results should be interpreted as exploratory.

4. Results

4.1. Ranking of Critical Success Factors

Table 3 (Appendix 1) presents mean scores and ranking of all 38 CSFs (top 10 and bottom 10 shown for brevity). The three factors perceived as most critical were: Appropriate team skills and knowledge (CSF23,

Table 2: Demographic information

Table 2. Demographic Information of Respondents		
Main variable specific variable	Frequency	%
Nature of procurement		
procurement services	32	45%
procurement goods	24	34%
procurement works	15	21%
Years of experience		
Less than 5 years	27	38%
6-10 years	29	41%
10-15 years	11	15%
more than 15 years	4	6%
Educational qualification		
HND	12	17%
B.Sc.	45	63%
M.Sc.	14	20%
Rank		
Senior management	11	15%
Middle management	27	38%
Low management	22	31%
Operational level	11	15%
Total	71	100%
Source: Author's own work		

3.2. Data Analysis

Data were analysed using SPSS version 22. Descriptive statistics (mean, standard deviation) ranked the 38 CSFs. Exploratory Factor Analysis (EFA) identified underlying latent structure using Principal Component Analysis (PCA) with Varimax rotation. Factor

$M=4.04$), Adequate technical know-how in AI tools (CSF20, $M=4.02$), and Adequate knowledge of AI applications (CSF19, $M=4.00$). This emphasises human capital and technical competence as immediate prerequisites.

4.2. Exploratory Factor Analysis

EFA extracted ten components with eigenvalues >1.0, explaining 76.13% of total variance. Table 4 presents the rotated component structure.

public sector reality where basic digital literacy remains limited.

The ten-component EFA model provides empirical support for the TOE framework, with components

Table 4: Exploratory factor analysis results

Component	Proposed Theme	Eigenvalue	Variance%	α
1	Internal Process & Team Coordination	12.434	32.72	0.891
2	Data Infrastructure & Ecosystems	3.237	8.52	0.867
3	Strategic Leadership & Governance	2.49	6.55	0.799
4	Vendor Partnership & System Integration	1.998	5.26	0.845
5	Early-Stage Planning & Alignment	1.949	5.13	0.812
6	User Competence & Workflow Adoption	1.627	4.28	0.784
7	Data Governance & Algorithmic Quality	1.52	4.00	0.741
8	Project Clarity & Organisational Readiness	1.358	3.57	0.784
9	Executive Support & Financial Resources	1.196	3.15	0.623
10	Technical Compatibility & Vendor Reliance	1.123	2.95	0.705

Note: Extraction Method: Principal Component Analysis. Rotation: Varimax with Kaiser Normalization. KMO = .772. Bartlett's Test: $\chi^2 = 1880.108$, $df = 703$, $p < .001$. Factor loadings <0.5 suppressed.

4.3. Interpretation of the Empirical Model

The ten-component model offers a granular structure for AI implementation. Component 1 (Internal Process & Team Coordination, $\alpha=0.891$) captures organisational mechanisms including role clarity, team collaboration, and change management. Interpretation: Respondents saw internal processes, team coordination, and technological infrastructure as inseparable—addressing technology alone without clear roles is insufficient.

Components 2 (Data Infrastructure, $\alpha=0.867$) and 7 (Data Governance, $\alpha=0.741$) distinguish having data from managing data properly. Interpretation: In Nigerian MDAs, fragmented databases mean data infrastructure and governance require different capabilities.

Components 3 (Strategic Leadership, $\alpha=0.799$) and 9 (Executive Support, $\alpha=0.623$) address leadership dimensions. Components 4, 5, and 10 capture external collaboration. Components 6 and 8 focus on human and project dimensions. The model reveals that success requires simultaneous attention to strategic, organisational, human, collaborative, and technical fronts.

5. Discussion

The finding that human capital factors (CSF23, CSF20, CSF19) rank as top three CSFs underscores that in the Nigerian public procurement context, workforce readiness precedes technological investment. This aligns with Makarius et al. (2020), who argued that AI adoption fails without corresponding investment in employee skills. However, it diverges from Merhi (2023), who found data management primary in private sector adoption. This contrast likely reflects Nigeria's

distributed across technological (Components 2, 7, 10), organisational (1, 3, 6, 8, 9), and environmental (4, 5) dimensions. The separation of Data Infrastructure (Component 2) from Data Governance (Component 7) is a novel contribution not explicitly identified in prior studies (e.g., Wuni, 2025). This likely reflects a specific challenge in Nigerian MDAs: fragmented legacy databases mean having data and managing data require different capabilities.

The relatively low loading of financial resources (Component 9, $\alpha=0.623$, 3.15% variance) suggests financial constraints, while present, are not perceived as the primary barrier. This contradicts assumptions that funding is the main obstacle in developing economies. Instead, human capital and process factors appear more critical.

A limitation of the current model is the modest reliability of Component 9 ($\alpha=0.623$), containing only two items. Future research should expand measurement of executive support and financial resources.

6. Practical Applications and Recommendations

The ten-component model serves as a diagnostic tool for public procurement agencies.

For policymakers at federal MDA level:

Prioritise AI skills training programmes over immediate technology procurement. Invest in certified AI literacy courses for procurement officers before purchasing AI software.

Establish a national data governance framework for public procurement, including mandatory data quality standards.

For procurement agency heads:

Conduct readiness assessments using the ten components as a checklist. If Component 2 (Data Infrastructure) scores low, prioritise data cleaning before AI vendor selection.

Require AI vendors to demonstrate knowledge transfer and training plans to avoid vendor reliance (Component 10).

For quantity surveyors and procurement officers:

Develop internal AI competency working groups addressing Component 6 (User Competence) through peer learning.

Document early planning decisions (Component 5) to ensure alignment between AI objectives and procurement strategy.

For international readers, the ten-component model is transferable but requires local calibration.

7. Conclusion and Limitations

This study assessed critical success factors for AI implementation in Nigerian public procurement. The top three CSFs prioritise human capital (team skills, technical know-how, AI knowledge). The empirically derived ten-component model (76.13% variance explained) provides a structured blueprint

distinguishing technological, organisational, and environmental dimensions.

Limitations: The sample (N=71) is modest for EFA, and findings are specific to Nigeria's federal MDA context. The cross-sectional design captures perceptions, not actual implementation outcomes.

Future research: Validate the ten-component model using confirmatory factor analysis with a larger, cross-national sample. Conduct longitudinal studies testing whether these CSFs predict actual AI adoption success. Investigate causal relationships among components (e.g., does Strategic Leadership predict Internal Process Coordination?).

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Appendix 1

Table 3: Descriptive statistics (top 10 and bottom 10 CSFs)

Descriptive statistic					
Code	Critical Success Factors	N	Mean	Std. Deviation	Rank
CSF23	Appropriate team skills and knowledge	71	4.04	1.075	1
CSF20	Adequate technical know-how and skills in AI tools	71	4.02	0.965	2
CSF19	Adequate knowledge of AI applications and requirements in the project	71	4.00	1.056	3
CSF17	Appropriate AI techniques and tools	71	3.97	1.171	4
CSF21	Strong expertise and experience of the AI developers	71	3.92	0.89	5
CSF24	Appropriate integration of AI with legacy systems	71	3.89	1.008	6
CSF18	Adequate computing capabilities and infrastructure in the project	71	3.76	0.992	7
CSF13	Alignment of AI with project strategy and business needs	71	3.70	1.101	8
CSF12	Clear vision and clarity of business case for AI	71	3.58	1.009	9
CSF30	Early involvement of AI consultant and vendors	71	3.58	1.051	10
CSF29	Early commitment of the client to AI in the project	71	3.56	1.092	11
CSF22	Robust integration of AI into workflow and processes	71	3.59	0.994	12
CSF34	Cyber security of data, infrastructure and algorithms	71	3.59	0.979	13
CSF38	Adequate data storage capacity and cloud resources	71	3.46	1.012	14
CSF33	Effective data management and governance strategy	71	3.48	1.054	15
CSF32	High quality and integrity of data for AI models	71	3.52	0.939	16
CSF25	Appropriate AI algorithms and models	71	3.51	1.026	17
CSF35	Availability and accessibility of high-value data	71	3.51	1.081	18
CSF31	Early commitment and collaboration of a cross-functional team	71	3.49	1.132	19
CSF15	Supportive organizational infrastructure	71	3.31	1.129	20
CSF10	Extensive front-end planning for AI integration	71	3.31	1.116	21
CSF26	Technical compatibility of AI with existing infrastructure	71	3.31	1.064	22
CSF16	Robust supportive technological infrastructure	71	3.42	1.009	23
CSF11	Effective change management strategy for AI integration	71	3.42	1.078	24
CSF37	Sufficient quantity and flow of data for AI models	71	3.44	1.131	25
CSF6	Conducive organisational culture for AI	71	3.44	1.038	26
CSF7	Sufficient organisational readiness for AI	71	3.37	0.989	27
CSF14	Clear and realistic objectives of AI in the project	71	3.39	0.948	28
CSF8	Clear assignment of roles, responsibilities and accountabilities for AI	71	3.21	1.054	29
CSF4	Effective AI leadership and governance	71	3.14	1.257	30
CSF3	Effective risk management for AI technologies	71	2.99	1.153	31
CSF2	Managerial competence and capabilities in AI	71	2.99	0.978	32
CSF1	Clear strategy and business model for AI	71	2.85	1.499	33
CSF9	Top management commitment and support	71	3.31	1.129	34
CSF27	Familiarity of the project team with AI tools in the project	71	3.27	1.121	35
CSF28	Support from qualified AI vendors	71	3.27	1.183	36
CSF36	Robust data ecosystems	71	3.44	1.119	37
CSF5	Adequate financial resources allocation for AI technologies	71	3.35	1.255	38