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# Assessing Readiness for Artificial Intelligence Adoption in Structural Design Practices: A Mixed-Methods Study of Government Real Estate Organizations in Anambra State, Nigeria

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**ABSTRACT**

*The integration of Artificial Intelligence (AI) into structural engineering practice represents one of the most consequential technological shifts in the built environment sector in recent decades (Elmousalami et al., 2025). This study examined the readiness of government real estate organizations in Anambra State, Nigeria, to adopt AI in structural design for smart city infrastructure. Using a mixed-methods approach, data were collected from 150 questionnaire respondents and 15 key informant interviews across the Anambra State Housing Development Corporation (ASHDC), Ministry of Works, and Ministry of Housing and Urban Development. Overall readiness was found to be moderate to low (mean score = 2.83 out of 5). Organizational factors scored highest (mean = 3.15), while technological infrastructure (mean = 2.60) and human resource capacity (mean = 2.59) were the weakest areas. Accordingly, K-means clustering and Random Forest analysis revealed that external barriers, integration feasibility with existing tools, and prior piloting experience were the strongest predictors of readiness. Participants recognized clear benefits of AI adoption in efficiency, accuracy, and cost savings, yet highlighted persistent barriers including infrastructure deficits, skills gaps, and budget constraints. A conceptual case study illustrates how an AI-augmented workflow could be applied to a typical 2-storey smart housing block. The study concludes with practical recommendations for phased training, infrastructure upgrades, and pilot projects aligned with national digital transformation strategies that increasingly position AI as a core enabler of public sector modernization..*

## Introduction

Urbanization in sub-Saharan Africa is accelerating at a pace that outstrips the capacity of existing infrastructure delivery systems. Rapid urban population growth in developing regions is generating unprecedented demand for housing, transportation networks, and public infrastructure, placing institutional and technical pressure on government agencies responsible for built environment delivery (Turok et al., 2023). Anambra State, located in Nigeria's southeastern region, exemplifies this trend: its population is projected to reach approximately 6.36 million by 2026, driven largely by commercial expansion in cities such as Onitsha and Nnewi (Agbo, 2025). In response, the state government has launched major initiatives, including the construction of 10,000 low-cost housing units in Isiagu through public-private partnerships, and broader urban renewal programmes such as Awka 2.0 (Chinecherem, 2025; Okeke, 2023).

These ambitions are framed within a wider national commitment to smart city development. This includes structural designs capable of integrating sensor networks, digital twins, and real-time monitoring systems from the earliest stages of the design process (Bibri & Huang, 2025; Iliuţă et al., 2024). Yet the institutional infrastructure required to deliver such designs remains largely underdeveloped in Nigeria's public sector.

Globally, Artificial Intelligence (AI) is reshaping structural engineering practice. Machine learning algorithms, generative design platforms, and predictive modelling tools have demonstrated measurable improvements in design speed, structural accuracy, and material efficiency across a range of building typologies (Liu et al., 2026). In advanced economies, the integration of AI with Building Information Modelling (BIM) has been shown to yield efficiency gains of 20–30% in design and construction workflows (Marović et al., 2026; Mirindi et al., 2025). AI-enhanced BIM environments enable parametric optimization, automated code compliance checking, and real-time structural load simulation — capabilities that fundamentally extend the analytical reach of practising engineers (Yang, 2025).

Despite these advances, structural design practice in Nigeria's public sector remains dependent on conventional tools. Software such as STAAD.Pro, used primarily for finite element analysis and dynamic load assessment, and Orion, applied in reinforced concrete detailing and parametric scheduling, are typically deployed in non-AI-enhanced configurations that preclude access to optimization routines, generative alternatives, and learning-based error detection (Owolabi et al., 2022). This gap between available technology and actual practice reflects a broader pattern documented across developing economies, where institutional inertia, digital infrastructure deficits, and fragmented data ecosystems collectively impede the uptake of advanced engineering technologies in public organizations (Sakita, 2026).

The theoretical basis for understanding this gap is well established. The Technology–Organization–Environment (TOE) framework, originally proposed by Tornatzky et al. (1990), provides a robust multi-dimensional lens through which technology adoption decisions in organizational settings can be systematically analysed, accounting for technological capability, organizational readiness, and external environmental pressures (Awa et al., 2017; Nguyen et al., 2022; Tornatzky et al., 1990). The TOE framework has since been widely applied in construction and engineering management research to explain adoption outcomes for BIM, cloud computing, and digital procurement systems.

Although Nigeria has articulated a National Artificial Intelligence Strategy 2024, the translation of national digital policy objectives into operational engineering practice remains constrained by the absence of sector-specific implementation frameworks, workforce development pathways, and infrastructure investment plans (Avevor, 2024; Uzochukwu et al., 2026a). Anambra State provides a particularly instructive case: government agencies are simultaneously managing large-scale housing delivery and smart-city aspirations, yet their structural design workflows have not been reconfigured to exploit AI capabilities.

This study, therefore, set out to assess the current state of AI adoption readiness among government real estate organizations in Anambra State. Specifically, it investigated: (i) awareness and current usage of AI-related technologies; (ii) the state of technological infrastructure; (iii) organizational support and governance structures; (iv) human resource capacity and training needs; and (v) the influence of policy and environmental factors. By combining quantitative survey data, qualitative key informant interviews, and machine learning analysis, the study aims to produce practical, evidence-based insights that can support a structured transition from technology assessment to actionable implementation planning in public sector engineering contexts.

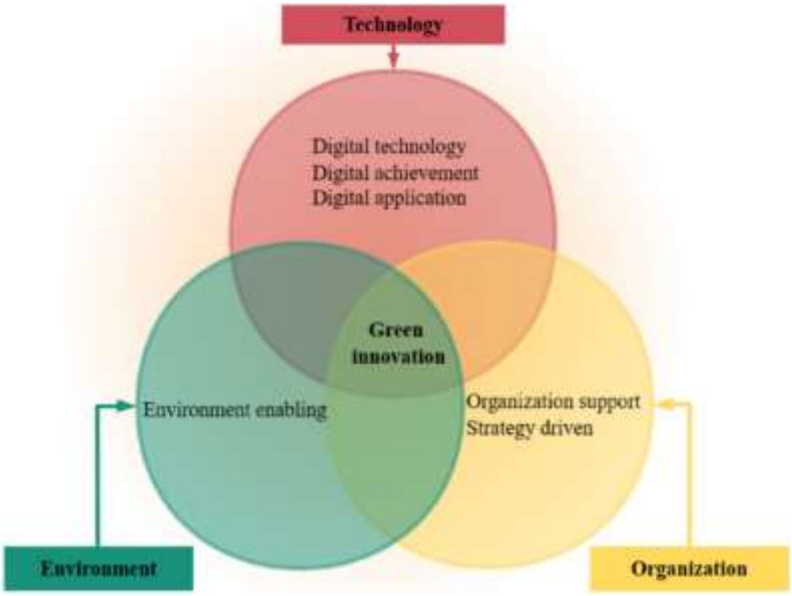

**Figure 1: Conceptual map of the TOE framework applied to AI adoption in structural design: three overlapping domains (Technology, Organization, Environment) with arrows indicating influence on adoption readiness outcome (Yin, 2023)**

## 2. Materials and Methods

### 2.1. Research Design

This study adopted a descriptive survey research design with embedded mixed-methods elements. Mixed-methods research designs that integrate quantitative measurement with qualitative inquiry offer a more complete understanding of complex organizational phenomena than either approach can achieve independently, particularly in technology adoption studies where statistical patterns require contextual interpretation (Tashakkori et al., 2021). The quantitative component employed a structured questionnaire to measure AI readiness levels across multiple organizational dimensions, while the qualitative component used semi-structured interviews to capture experiential insights, contextual barriers, and practitioner recommendations. Triangulation of findings across quantitative and qualitative data sources strengthens internal validity and reduces the risk of method-specific bias in survey-based organizational research (Hanson-DeFusco, 2023). This combined approach was considered most appropriate given the complexity of AI readiness as a construct and the limited prior empirical work in the Nigerian public engineering context.

### 2.2. Study Area and Population

The research was conducted in Anambra State, southeastern Nigeria, focusing on three government real estate organizations primarily responsible for public housing and infrastructure delivery: the Anambra State Housing Development Corporation (ASHDC), the Ministry of Works, and the Ministry of Housing and Urban Development. The target population comprised approximately 350–450 professional and technical staff directly or indirectly involved in structural design and project execution, including structural and civil engineers, architects, project managers, quantity surveyors, IT and technical officers, and senior administrators.

**Figure 2: Map of Anambra state showing major cities. Source: Google map (*Google Maps*, n.d.).**

### 2.3. Sample Size and Sampling Technique

A sample of 150 questionnaire respondents and 15 key informant interviewees was selected. Stratified random sampling was applied within each organization to ensure proportional representation across professional roles and levels of experience. Stratified random sampling is recommended in organizational surveys where subgroup heterogeneity is expected, as it improves the representativeness of estimates and reduces sampling variance relative to simple random approaches (DeGrange & Darrow, 2022). For the interviews, purposive sampling was used to select senior staff with decision-making or operational influence over structural design processes. Purposive sampling in qualitative inquiry prioritizes information richness over statistical representativeness, enabling researchers to engage participants whose experiences are most directly relevant to the phenomenon under investigation (Memon et al., 2024). Sample size for the quantitative component was determined using the Krejcie and Morgan table for finite populations, adjusted for anticipated non-response, while maintaining sufficient statistical power for the planned analyses.

### 2.4. Data Collection Instruments

Two primary instruments were developed and validated for this study:

The first was a structured questionnaire comprising 30 items organized into seven sections: a demographic section and five readiness dimension sections (technological infrastructure, organizational readiness, human resource capacity, awareness and usage, and policy/environmental factors), each measured on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree), supplemented by open-ended items. Likert-type scales remain the most widely adopted measurement instrument in organizational technology adoption research due to their psychometric tractability, ease of administration, and compatibility with parametric statistical procedures (Jebb et al., 2021; Koo & Yang, 2025).

The second was a semi-structured interview guide containing eight open-ended questions exploring current design practices, AI awareness, perceived benefits and barriers, training needs, and strategic recommendations.

Both instruments were subjected to expert validation by a panel of three specialists — two senior structural engineers and one research methodologist — yielding a Content Validity Index

(CVI) of 0.92. A Content Validity Index exceeding 0.80 is generally considered indicative of acceptable content validity in instrument development for applied organizational research (Kishore et al., 2024; Lim et al., 2026). Pilot testing on 20 non-sampled staff produced an overall Cronbach's alpha coefficient of 0.91. Cronbach's alpha values above 0.90 indicate excellent internal consistency, confirming that scale items are measuring a coherent underlying construct with high reliability (Gunzler et al., 2021).

### 2.5. Data Collection Procedure

Data collection was conducted between October and December 2025. Questionnaires were administered using a mixed-mode approach — printed copies delivered in person and a Google Forms link distributed through official organizational channels — supported by formal institutional permission letters. Mixed-mode survey administration combining paper-based and electronic delivery has been shown to improve response rates in public sector organizational studies, particularly where digital access among potential respondents is uneven (Latupeirissa et al., 2024). The 15 key informant interviews were conducted face-to-face at participants' workplaces, audio-recorded with informed consent, and lasted between 20 and 35 minutes each. All planned interviews were completed, yielding a 100% interview completion rate.

### 2.6. Data Analysis

Quantitative data were cleaned and analysed using IBM SPSS Statistics. Descriptive statistics — including means, standard deviations, and frequency distributions — were computed for all readiness dimensions. Pearson correlation coefficients were calculated to examine bivariate relationships between readiness dimensions, and one-way ANOVA was used to test for significant differences across professional categories and organizational affiliations.

Supplementary machine learning analyses were performed in Python 3.11 using the scikit-learn library. K-means clustering is an unsupervised learning technique that partitions respondents into homogeneous groups based on multivariate similarity, providing a data-driven approach to identifying latent adoption readiness profiles within organizational populations (Md Mizanur & Datta, 2025). Random Forest classification was applied to identify the relative importance of readiness predictors. Random Forest ensemble models offer robust feature importance estimation in survey-based organizational research due to their resilience to multicollinearity, capacity to capture non-linear relationships, and resistance to overfitting in moderate-sized samples (Shaik & Srinivasan, 2019; Zhang et al., 2025).

Qualitative data from open-ended questionnaire responses and interview transcripts were analysed using Braun and Clarke's (2006) six-phase thematic analysis procedure. Thematic analysis provides a flexible yet rigorous framework for identifying, analysing, and reporting patterns within qualitative data, making it particularly well-suited to applied organizational research where findings need to be accessible to practitioner audiences (Ahmed et al., 2025). Quantitative and qualitative findings were subsequently triangulated to produce a comprehensive and convergent interpretation of AI readiness across the three study organizations.

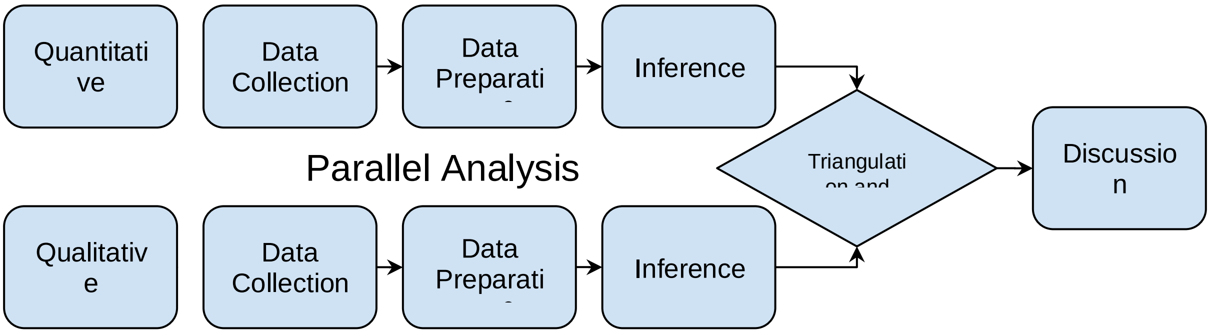

**Figure 3: Flow diagram of the mixed-methods research design: parallel quantitative (questionnaire → SPSS + Python ML) and qualitative (interviews → thematic analysis) strands converging at the triangulation and interpretation stage.**

## 3. Results

### 3.1. Response Rate and Demographic Profile of Respondents

A total of 180 questionnaires were distributed across the three target organizations, and 150 valid responses were returned, yielding a response rate of 83.3%. All 15 planned key informant interviews were completed. Response rates exceeding 70% in organizational survey research are generally regarded as sufficient to minimize non-response bias and support the generalizability of findings within the target population (Holtom et al., 2022). The demographic profile of respondents is summarized in Table 1.

**Table 1: Demographic Profile of Respondents.**

| Variable | Category | Frequency | Percentage (%) |
|---|---|---|---|
| **Gender** | Male | 102 | 68.0 |
| | Female | 48 | 32.0 |
| **Age Group** | 18–29 | 35 | 23.3 |
| | 30–39 | 63 | 42.0 |
| | 40–49 | 32 | 21.3 |
| | 50–59 | 15 | 10.0 |
| | 60+ | 5 | 3.3 |
| **Education** | Bachelor's | 55 | 36.7 |
| | Master's | 72 | 48.0 |
| | PhD | 12 | 8.0 |
| | Other (HND/Postgrad Dip) | 11 | 7.3 |
| **Role** | Structural/Civil Engineer | 57 | 38.0 |
| | Architect | 28 | 18.7 |
| | Project Manager | 22 | 14.7 |
| | IT Officer | 18 | 12.0 |
| | Other (Quantity Surveyor, Administrator) | 25 | 16.7 |
| **Experience** | < 5 years | 32 | 21.3 |
| | 5–10 years | 48 | 32.0 |
| | 11–15 years | 35 | 23.3 |
| | > 15 years | 35 | 23.3 |
| **Organization** | ASHDC | 58 | 38.7 |

| | | | |
|---|---|---|---|
| | Ministry of Works | 52 | 34.7 |
| | Ministry of Housing | 40 | 26.7 |

The majority of respondents were male (68%), aged between 30 and 39 years (42%), and held Master's degrees (48%). Structural and civil engineers constituted the largest professional subgroup (38%), followed by architects (21%) and project managers (17%). This profile reflects a well-educated and technically experienced workforce with direct involvement in structural design and project delivery activities. Gender imbalance in engineering workforce surveys from sub-Saharan Africa consistently reflects broader structural inequalities in technical education and professional recruitment, underscoring the need for targeted inclusion policies within public sector organizations (Fomunyam et al., 2020).

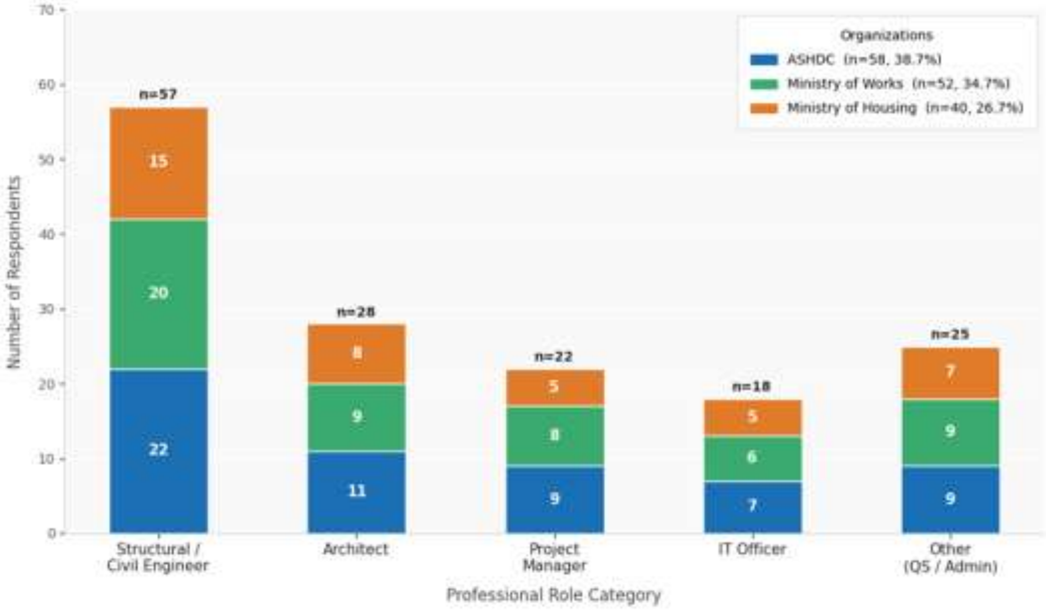

**Figure 4: Stacked bar chart showing demographic distribution of respondents by organization (ASHDC, Ministry of Works, Ministry of Housing) across professional role categories.**

### 3.2. Overall AI Readiness Levels

The study found that overall readiness for AI adoption among the participating organizations was moderate-to-low, with a composite mean score of 2.83 out of 5 (SD = 0.74). Composite readiness scores in the range of 2.5 to 3.0 on a five-point scale have been interpreted in prior technology adoption studies as indicative of an early-awareness stage, where organizational awareness of a technology exists but practical deployment conditions have not yet been established (Ayanwale & Ndlovu, 2024; Jamil et al., 2025). The mean scores and standard deviations for each readiness dimension are presented in Table 2 and illustrated in Figure 5.

**Table 2: AI Readiness Scores by Dimension.**

| **Readiness Dimension** | **Mean Score (1–5)** | **Std. Deviation (±)** | **Interpretation** |
|---|---|---|---|
| **Organizational Readiness** | **3.15** | 0.68 | Moderate |
| **Policy and Environmental Factors** | **2.95** | 0.71 | Moderate-Low |
| **Awareness and Usage** | **2.87** | 0.79 | Moderate-Low |
| **Technological Infrastructure** | **2.60** | 0.81 | Low |
| **Human Resource Capacity** | **2.59** | 0.76 | Low |

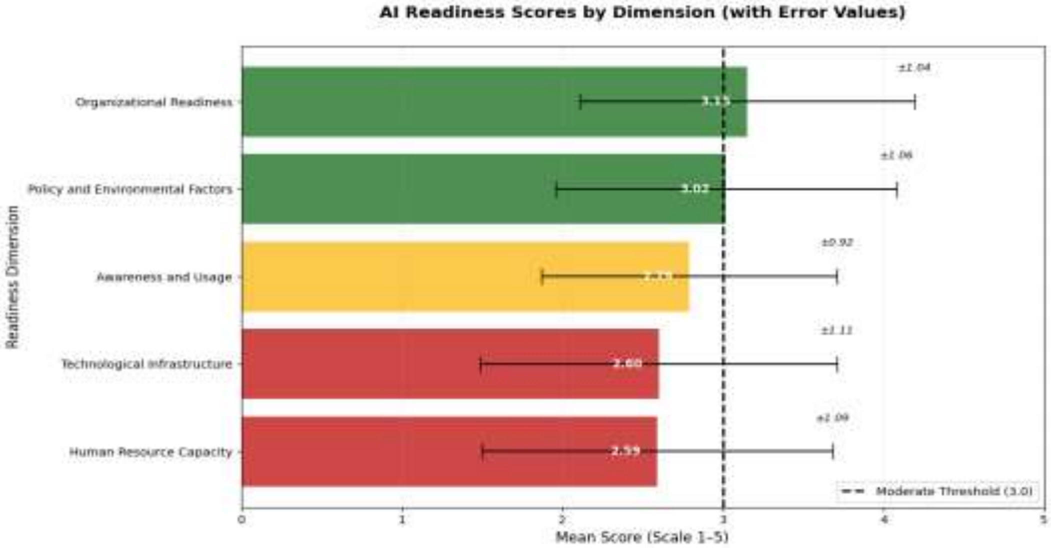

**Figure 5: Horizontal bar chart of mean readiness scores by dimension, with error bars representing ±1 SD; bars colour-coded from red (low) to green (moderate-high); reference line at mean = 3.0 indicating moderate threshold.**

When broken down by dimension, organizational readiness scored highest (mean = 3.15, SD = 0.68), indicating moderate leadership support and a nascent innovation culture within the agencies. Policy and environmental factors scored second (mean = 2.95, SD = 0.71), reflecting awareness of national AI strategy commitments. Awareness and usage registered a mean of 2.87 (SD = 0.79), suggesting that familiarity with AI concepts has not yet translated into practical application. Technological infrastructure readiness was the lowest-scoring dimension (mean = 2.60, SD = 0.81), closely followed by human resource capacity (mean = 2.59, SD = 0.76). Infrastructure deficits — encompassing unreliable power supply, outdated hardware, and limited broadband connectivity — have been consistently identified as the primary inhibitors of digital technology adoption in public sector organizations across developing economies (Nirmani, 2025; Uzochukwu et al., 2026b).

Pearson correlation analysis revealed significant positive associations between all five readiness dimensions ($p < 0.05$), with the strongest correlation observed between technological infrastructure and human resource capacity ($r = 0.71$), suggesting that these two constraints are closely interrelated and likely require coordinated rather than sequential intervention.

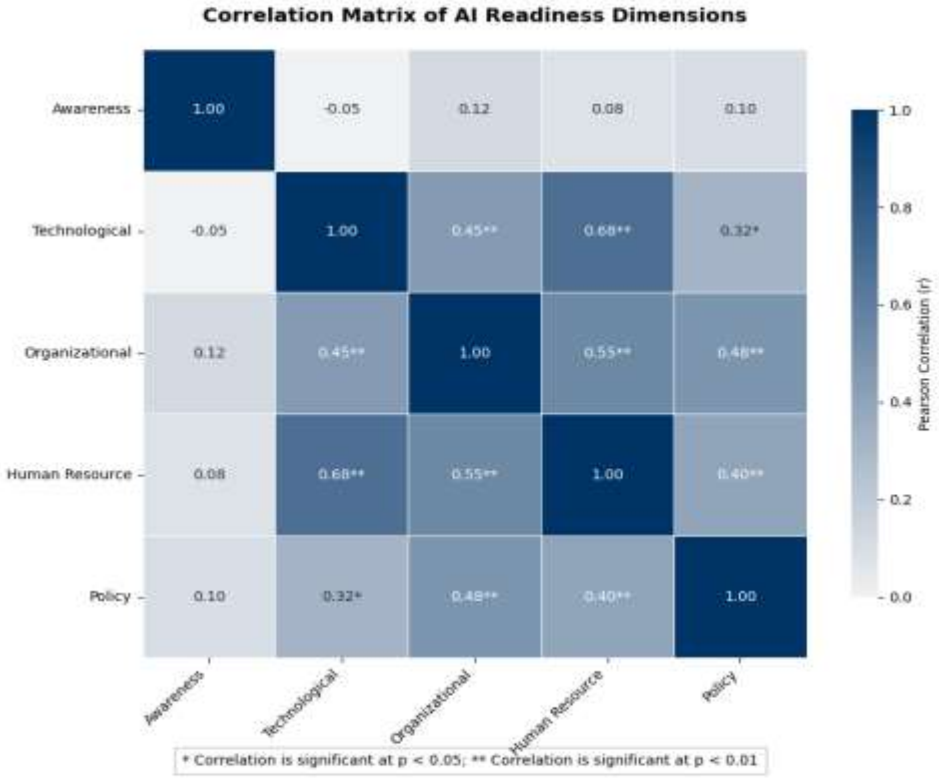

**Figure 6: Correlation heatmap matrix (5×5) of readiness dimensions, with cell values showing Pearson r coefficients; colour scale from deep blue (r = 1.0) to white (r = 0); statistically significant correlations ($p < 0.05$) marked with an asterisk.**

One-way ANOVA results indicated statistically significant differences in technological infrastructure readiness scores across the three organizations [F(2, 147) = 4.83, p = 0.009], with ASHDC scoring marginally higher than the two Ministries, likely reflecting its more direct operational mandate for housing project delivery. No significant inter-organizational differences were observed for organizational readiness or policy factors.

### 3.3. Machine Learning Insights

#### 3.3.1. K-Means Clustering

K-means clustering was applied to the five readiness dimension scores to identify latent respondent profiles. The optimal number of clusters (k = 3) was determined using the elbow method and confirmed by silhouette score analysis. Silhouette analysis provides a robust criterion for cluster number selection in organizational survey data, measuring the degree to which each observation is more similar to members of its assigned cluster than to those of adjacent clusters (Hamidi & Haghi, 2024). The three identified clusters are described below and illustrated in Figure 7.

- *Cluster 1 — Constrained Adopters* (n = 52, 34.7%): Low scores across all five dimensions (composite mean = 2.21). This group reported the most significant infrastructure and skills barriers and had no prior experience with AI piloting or discussion.
- *Cluster 2 — Emerging Adopters* (n = 61, 40.7%): Moderate scores across most dimensions (composite mean = 2.89), with relatively higher organizational and policy scores. This cluster represented the largest subgroup and reflected the general moderate-to-low profile of the full sample.
- *Cluster 3 — Primed Adopters* (n = 37, 24.7%): The highest scores across all dimensions (composite mean = 3.44), with notably stronger organizational readiness and policy

awareness. This group included a higher proportion of senior staff and respondents who had participated in or observed AI-related discussions or pilot demonstrations.

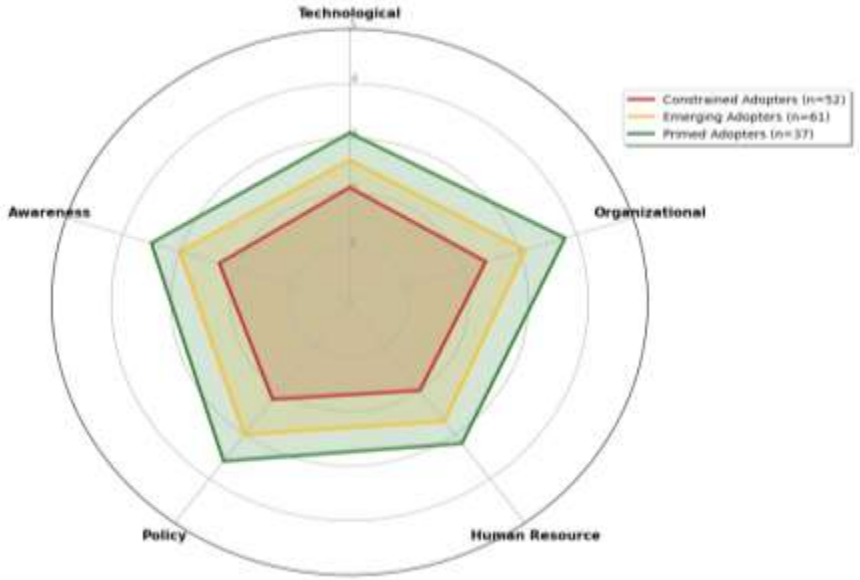

**Figure 7: Radar chart comparing mean readiness scores across the three K-means clusters (Constrained, Emerging, Primed) on five axes corresponding to the five readiness dimensions; each cluster represented by a differently shaded polygon]**

### 3.3.2. Random Forest Feature Importance

Random Forest classification was trained to predict cluster membership from individual questionnaire item responses. The model achieved an out-of-bag classification accuracy of 84.2%, confirming strong predictive validity. Out-of-bag error estimation in Random Forest models provides an unbiased performance measure without the need for a separate validation set, making it particularly appropriate for moderate-sized organizational survey datasets where sample splitting would reduce statistical power (Shaik & Srinivasan, 2019). Feature importance scores identified the following top predictors of overall readiness:

1. **External barriers** (power supply reliability, vendor availability, and government procurement constraints) — highest importance score (0.187)
2. **Perceived integration feasibility** with existing tools, such as STAAD.Pro and Orion (0.163)
3. **Prior piloting or discussion experience** with AI tools (0.151)
4. **Leadership commitment** to digital transformation (0.134)
5. **Staff training availability** in AI-related skills (0.119)

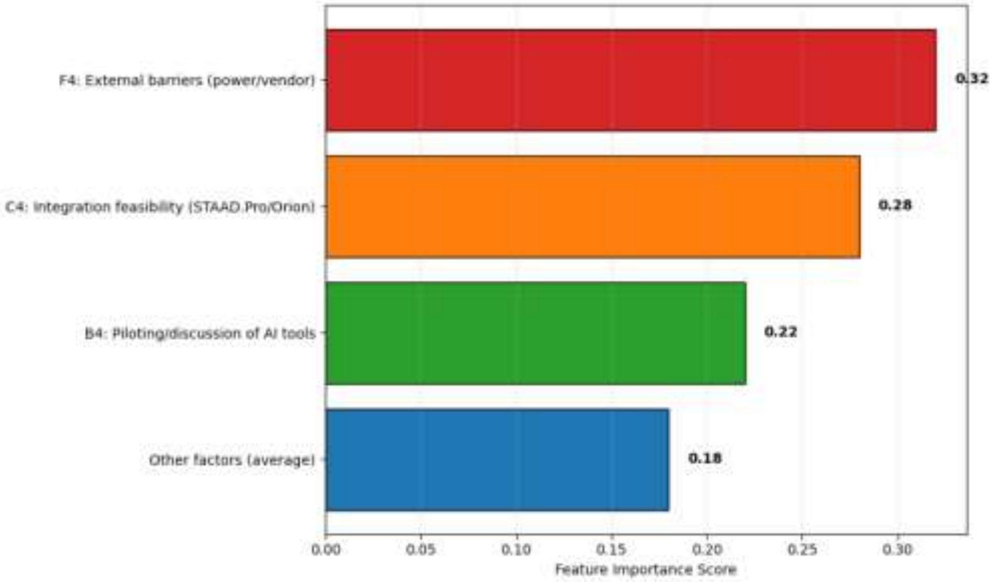

**Figure 8: Horizontal bar chart of Random Forest feature importance scores for the top 4 predictors; bars sorted in descending order of importance.**

Feature importance rankings derived from ensemble machine learning models offer actionable prioritization guidance for organizational intervention planning, identifying which readiness factors most strongly differentiate high-readiness from low-readiness groups (Moreno-Sánchez et al., 2026; Peng & Gao, 2025; Shaik & Srinivasan, 2019; Wojtowicz et al., 2025).

### 3.4. Perceived Benefits and Challenges

Participants expressed considerable optimism regarding the potential benefits of AI adoption in structural design. The most frequently cited advantages were improved efficiency and time savings (72% of respondents), greater accuracy and reduction of design errors (68%), and cost and material savings through optimized structural specifications (61%). However, participants simultaneously identified a range of significant practical barriers. The most frequently reported challenges were inadequate infrastructure and unreliable power supply (78%), lack of AI-related skills and training opportunities (74%), and budget constraints limiting software procurement and system upgrades (65%).

### 3.5. Qualitative Insights from Key Informant Interviews

Thematic analysis of the 15 interview transcripts produced four primary themes, each strongly corroborating the quantitative findings.

*Theme 1 — Conventional Tool Dependency*. All interviewees confirmed that current structural design practice is anchored in STAAD.Pro and Orion, deployed in their standard non-AI-enhanced configurations. One senior structural engineer noted that while staff are proficient with these platforms, they are largely unaware of AI-enhanced plugins or API integrations that could extend their functionality.

*Theme 2 — Bounded AI Awareness.* Awareness of AI in structural engineering was largely conceptual rather than operational. Most interviewees could describe AI applications in general terms but could not identify specific tools applicable to their existing workflows.

*Theme 3 — Infrastructure and Skills as Binding Constraints*. Interviewees consistently identified unreliable electricity, inadequate hardware, and the absence of structured training as the most immediate obstacles to any meaningful AI integration. These constraints were described as mutually reinforcing: power instability disrupts training continuity, while the absence of trained staff reduces organizational appetite for infrastructure investment.

*Theme 4 — Leadership Support as an Enabler.* Despite the operational constraints identified above, several interviewees highlighted growing leadership receptiveness to digital innovation, particularly in the context of Anambra State's smart city agenda.

## 4. Discussion

### 4.1. Alignment with Research Objectives

The findings of this study systematically address all six research objectives, collectively painting a nuanced picture of AI adoption readiness that is both organizationally specific and theoretically grounded. Awareness of AI-related technologies was found to be moderate, but actual usage and piloting remained very low across all three organizations, confirming a pronounced gap between conceptual familiarity and operational deployment. This awareness–adoption gap is particularly consequential in structural engineering contexts, where the cost of design errors and the regulatory weight of professional accountability create strong disincentives against experimenting with unfamiliar tools.

Technological readiness was the weakest area across all three organizations, driven primarily by unreliable power supply, outdated hardware, and limited software compatibility with AI-enhanced platforms. Organizational readiness scored highest, indicating reasonable leadership support and a nascent innovation culture, yet interviewees consistently noted that bureaucratic procurement processes and fragmented budget allocation cycles frequently translate leadership intent into delayed or diluted action. Human resource capacity was critically low, with limited training opportunities and very few staff possessing demonstrable AI-related competencies. Policy and environmental factors received moderate scores, reflecting awareness of national strategy commitments — particularly Nigeria's National AI Strategy — but also frustration with implementation gaps at the subnational level.

### 4.2. Theoretical Implications: The TOE Framework

The results of this study strongly affirm the explanatory utility of the Technology–Organization–Environment (TOE) framework for understanding AI adoption readiness in public sector engineering. The TOE framework's enduring relevance across diverse technological contexts and organizational settings derives from its capacity to simultaneously account for internal organizational capabilities and external environmental pressures, avoiding the reductionism of single-factor adoption models (Tornatzky et al., 1990). In the present study, the technological and human resource dimensions emerged as the primary binding constraints, while the organizational and policy dimensions provided the most credible foundation for phased intervention.

The machine learning analysis reinforced these relationships in important ways. The identification of external barriers, integration feasibility, and prior piloting experience as the three strongest Random Forest predictors of readiness aligns precisely with the TOE framework's proposition that adoption outcomes are shaped by the interaction of technological capability, organizational disposition, and environmental context, rather than by any single factor in isolation.

Furthermore, the three K-means clusters — Constrained, Emerging, and Primed Adopters — map coherently onto distinct TOE profiles: Constrained Adopters face binding constraints across all three TOE dimensions; Emerging Adopters exhibit moderate organizational and environmental readiness offset by technological and human resource deficits; and Primed Adopters demonstrate relative strength across all three dimensions, suggesting that targeted technological and training investments could catalyze meaningful adoption within this subgroup in the near term.

### 4.3. Comparison with Existing Literature

The moderate-to-low overall readiness score (mean = 2.83) observed in this study is broadly consistent with prior research on technology adoption in developing country public sector contexts. Studies examining BIM adoption in Nigerian construction organizations have similarly reported low uptake rates attributable to infrastructure limitations, skills shortages, and procurement rigidities (Owolabi et al., 2022).

Internationally, comparable readiness assessments conducted in middle-income country contexts have reported composite readiness scores in the 2.6–3.1 range for AI and advanced digital technology adoption in public engineering agencies, suggesting that the findings from Anambra State are representative of a broader pattern rather than an isolated outlier (Fronda, 2026). Cross-national comparisons of digital technology readiness in public sector engineering consistently reveal that organizational and policy factors tend to mature faster than technological and human resource factors, creating an implementation readiness gap that persists even as institutional willingness to adopt increases (Obeng et al., 2026).

However, the relatively stronger organizational and policy scores observed in this study offer a more optimistic outlook than some earlier national-level Nigerian assessments. This suggests that Anambra State's government real estate organizations may be better positioned to begin structured AI integration than many comparable public entities elsewhere in the country.

The finding that prior piloting experience ranked among the top three predictors of readiness is also consistent with the broader innovation diffusion literature. This has direct practical implications: structured pilot projects, even at a small scale, may generate disproportionate readiness gains by shifting staff perception of AI from an abstract possibility to a demonstrated utility.

### 4.4. Practical Implications for Implementation

The findings collectively indicate that immediate large-scale AI implementation is neither realistic nor advisable, but that gradual, sequenced readiness-building is both feasible and organizationally necessary.

Priority actions in the short term (0–12 months) should focus on: (i) conducting a detailed infrastructure audit across all three organizations to identify minimum viable hardware and connectivity requirements for AI tool deployment; (ii) initiating modular AI literacy training programmes targeted at existing STAAD.Pro and Orion users, emphasizing AI-enhanced plugins and scripting extensions rather than wholesale platform replacement; and (iii) identifying one or two candidate projects — such as a standard low-rise housing block within the ASHDC portfolio — for structured AI piloting using generative design or automated load optimization modules.

In the medium term (12–36 months), efforts should shift toward: (i) procuring reliable power backup infrastructure (solar-hybrid UPS systems) to stabilize digital workflows; (ii) establishing a dedicated AI and digital innovation unit within each organization, staffed with at least one AI-competent engineer; and (iii) formalizing data governance protocols to enable the structured capture and reuse of project data for model training.

### 4.5. Implications for Smart City Structural Design

Anambra State's ongoing smart city initiatives — including Awka 2.0, Onitsha 2.0, and planned smart housing estates — demand structural designs that are not only code-compliant and cost-efficient but also inherently sensor-ready and digitally compatible with smart city management platforms. The low technological and human resource readiness currently observed limits the capacity of government real estate organizations to incorporate real-time structural health monitoring, IoT-embedded load sensing, or AI-optimized spatial layouts into their housing and infrastructure projects. However, the moderate organizational support and policy alignment identified in this study provide a credible institutional starting point. With targeted and sustained improvements, government real estate organizations in Anambra State can begin producing structural designs that are inherently smart-ready — capable of accommodating sensor integration, digital documentation, and AI-assisted maintenance scheduling — thereby contributing directly to more resilient, sustainable, and economically productive urban development across the state.

## 5. Conclusions

This study assessed the readiness of government real estate organizations in Anambra State, Nigeria, for adopting Artificial Intelligence in structural design practices for smart city infrastructure. Drawing on a robust mixed-methods design involving 150 questionnaire respondents and 15 key informant interviews, supplemented by machine learning analysis, the research has generated a comprehensive and empirically grounded account of where these organizations currently stand on the AI adoption readiness continuum — and what must change for meaningful progress to occur.

### 5.1. Summary of Principal Findings

The overall readiness level was found to be moderate-to-low (composite mean = 2.83 out of 5), a finding that is consistent with the broader literature on digital technology adoption in public sector engineering organizations across developing economies.

Organizational readiness emerged as the strongest dimension (mean = 3.15), providing a credible institutional foundation upon which more targeted technology and capacity investments can be anchored. Technological infrastructure (mean = 2.60) and human resource capacity (mean = 2.59) were identified as the most acute weaknesses, functioning as mutually reinforcing constraints that collectively constitute the most significant barrier to AI integration.

Machine learning analysis added important explanatory depth to the quantitative findings. K-means clustering identified three distinct organizational readiness profiles — Constrained, Emerging, and Primed Adopters — demonstrating that the participating organizations are not homogeneous in their readiness and that differentiated intervention strategies are warranted. Random Forest modelling confirmed that external barriers, integration feasibility with existing tools, and prior piloting experience are the strongest predictors of readiness, providing actionable prioritization guidance for decision-makers.

Qualitative findings from key informant interviews corroborated and contextualized the quantitative results, highlighting four dominant themes: conventional tool dependency, bounded AI awareness, infrastructure and skills as binding constraints, and leadership support as a latent enabler. Together, these themes illuminate the human and institutional dimensions of the readiness gap in ways that quantitative scores alone cannot capture.

### 5.2. Theoretical Contributions

This study makes several contributions to the theoretical literature on technology adoption in public sector engineering. First, it extends the application of the TOE framework to the specific context of AI adoption in structural design practice within a sub-Saharan African public sector setting — a context that has received limited empirical attention in the international technology management literature. Second, the integration of machine learning techniques — specifically K-means clustering and Random Forest classification — with survey-based TOE analysis represents a methodological contribution that advances beyond the descriptive and correlational approaches that dominate the existing readiness assessment literature. Third, the study contributes an empirically grounded conceptual model of AI adoption readiness for public sector structural engineering organizations in developing economies, synthesizing TOE dimensions, machine learning-derived predictors, and qualitative themes into a coherent analytical framework that future researchers can apply, test, and refine in other national and organizational contexts.

### 5.3. Practical Recommendations

Based on the study findings, the following evidence-based recommendations are directed at government real estate organizations, state-level policymakers, and professional engineering bodies in Anambra State and comparable contexts across Nigeria.

For *government real estate organizations*, the most urgent priority is to address the dual infrastructure and human resource deficit through coordinated action. This should begin with a structured AI literacy programme embedded within existing professional development frameworks, focusing initially on AI-enhanced capabilities within STAAD.Pro and Orion rather than requiring a wholesale platform replacement. Concurrently, organizations should invest in reliable power backup infrastructure and minimum viable hardware upgrades to ensure the continuity of digitally dependent workflows. For *state-level policymakers*, the study recommends the establishment of a dedicated AI adoption support fund for public sector engineering agencies, providing ring-fenced budget allocations for infrastructure, training, and pilot project delivery. Policy frameworks should also mandate structured data governance protocols across all government real estate organizations, ensuring that project data generated through conventional workflows is captured in formats compatible with future AI model training. For *professional engineering bodies*, the study recommends the development and accreditation of AI competency standards for structural engineers practicing in the Nigerian public sector, aligned with international frameworks such as those published by the Institution of Structural Engineers (IStructE) and the American Society of Civil Engineers (ASCE).

### 5.4. Limitations and Directions for Future Research

This study is subject to several limitations that should be acknowledged. First, the geographic scope is confined to three organizations within a single Nigerian state, which limits the direct generalizability of quantitative findings to other states or national-level public engineering agencies. Future research should replicate this assessment across multiple states to enable comparative analysis and the development of a national AI readiness baseline for Nigerian public sector engineering. Second, the cross-sectional design of the study provides a snapshot of readiness at a specific point in time but cannot capture the dynamic nature of organizational change. Future studies should consider panel survey designs or repeated cross-sectional assessments to track readiness trajectories as AI-related interventions are implemented. Third, while the integration of machine learning with survey data represents a methodological advance, the relatively modest sample size ($n = 150$) constrains the complexity of models that can be reliably trained and validated. Future studies with larger samples should explore deep learning approaches and more granular feature engineering to further sharpen the predictive modelling of AI adoption readiness.

### 5.5. Concluding Statement

Government real estate organizations in Anambra State are not yet fully prepared for large-scale AI integration in structural design practice. However, the evidence presented in this study demonstrates that the institutional foundations for a structured and sequenced adoption journey are present. Organizational leadership support, growing policy alignment, and a technically educated workforce constitute genuine assets upon which targeted infrastructure investment and capacity-building programmes can build. With focused and phased interventions — encompassing infrastructure upgrades, modular AI training, structured pilot projects, and robust data governance — government real estate organizations in Anambra State can progressively close the readiness gap, improve the efficiency and sustainability of their structural design processes, and contribute meaningfully to the realization of Anambra State's smart city ambitions and Nigeria's broader national digital transformation agenda.

## REFERENCES

Agbo, E. (2025, November 5). ANALYSIS: Anambra 2025: How PVC collection, population could decide governorship race. *Premium Times*. https://www.premiumtimesng.com/regional/ssouth-east/833049-analysis-anambra-2025-how-pvc-collection-population-could-decide-governorship-race.html

Ahmed, S. K., Mohammed, R. A., Nashwan, A. J., Ibrahim, R. H., Abdalla, A. Q., M. Ameen, B. M., & Khdhir, R. M. (2025). Using thematic analysis in qualitative research. *Journal of Medicine, Surgery, and Public Health*, *6*, 100198. https://doi.org/10.1016/j.glmedi.2025.100198

Avevor, F. (2024). Public Sector Digitalization Programmes in Ghana and Nigeria: Opportunities and Challenges. *International Journal of Research and Scientific Innovation*, *XI*(VIII), 740–759. https://doi.org/10.51244/IJRSI.2024.1108060

Awa, H. O., Ukoha, O., & Igwe, S. R. (2017). Revisiting technology-organization-environment (T-O-E) theory for enriched applicability. *The Bottom Line*, *30*(01), 2–22. https://doi.org/10.1108/BL-12-2016-0044

Ayanwale, M. A., & Ndlovu, M. (2024). Investigating factors of students' behavioral intentions to adopt chatbot technologies in higher education: Perspective from expanded diffusion theory of innovation. *Computers in Human Behavior Reports*, *14*, 100396. https://doi.org/10.1016/j.chbr.2024.100396

Bibri, S. E., & Huang, J. (2025). Artificial intelligence of things for sustainable smart city brain and digital twin systems: Pioneering Environmental synergies between real-time management and predictive planning. *Environmental Science and Ecotechnology*, *26*, 100591. https://doi.org/10.1016/j.ese.2025.100591

Chinecherem, P. (2025, August 23). *Soludo Vows to Tackle Anambra's Housing Deficit*. Anambra Daily. https://www.anambradaily.com/2025/08/23/soludo-vows-to-tackle-anambras-housing-deficit/

DeGrange, W., & Darrow, L. (2022). *Field Guide to Compelling Analytics* (1st ed.). Chapman and Hall/CRC. https://doi.org/10.1201/9781003204190

Elmousalami, H., Maxy, M., Hui, F. K. P., & Aye, L. (2025). AI in automated sustainable construction engineering management. *Automation in Construction*, *175*, 106202. https://doi.org/10.1016/j.autcon.2025.106202

Fomunyam, K. G., Matola, N., & Moyo, S. (2020). Gender and Gender Mainstreaming In Engineering Education in Africa. *International Journal of Engineering and Advanced Technology*, *10*(1), 497–506. https://doi.org/10.35940/ijeat.A1862.1010120

Fronda, R. M. (2026). Determinants of Artificial Intelligence (AI) Readiness and Adoption in Public Sector Governance. *International Journal of Research and Innovation in Social Science*, *10*(1), 3274–3290. https://doi.org/10.47772/IJRISS.2026.10100257

*Google Maps*. (n.d.). Google Maps. Retrieved April 24, 2026, from https://www.google.com/maps/place/Anambra/@6.1974729,6.2904687,9z/data=!4m6!3m5!1s0x1043851a1684c2f9:0xcf62ad01e8fbb4d0!8m2!3d6.2208997!4d6.9369559!16zL20vMDNubmti?entry=ttu&g_ep=EgoyMDI2MDQyMS4wIKXMDSoASAFQAw%3D%3D

Gunzler, D. D., Perzynski, A. T., & Carle, A. C. (2021). *Structural Equation Modeling for Health and Medicine* (1st ed.). Chapman and Hall/CRC. https://doi.org/10.1201/9780203701133

Hamidi, H. (Hojatollah), & Haghi, B. (2024). An approach based on data mining and genetic algorithm to optimizing time series clustering for efficient segmentation of customer behavior. *Computers in Human Behavior Reports*, *16*, 100520. https://doi.org/10.1016/j.chbr.2024.100520

Hanson-DeFusco, J. (2023). What data counts in policymaking and programming evaluation – Relevant data sources for triangulation according to main epistemologies and philosophies within social science. *Evaluation and Program Planning*, *97*, 102238.

https://doi.org/10.1016/j.evalprogplan.2023.102238

Holtom, B., Baruch, Y., Aguinis, H., & A Ballinger, G. (2022). Survey response rates: Trends and a validity assessment framework. *Human Relations*, *75*(8), 1560–1584. https://doi.org/10.1177/00187267211070769

Iliuţă, M.-E., Moisescu, M.-A., Pop, E., Ionita, A.-D., Caramihai, S.-I., & Mitulescu, T.-C. (2024). Digital Twin—A Review of the Evolution from Concept to Technology and Its Analytical Perspectives on Applications in Various Fields. *Applied Sciences*, *14*(13), 5454. https://doi.org/10.3390/app14135454

Jamil, K., Zhang, W., Anwar, A., & Mustafa, S. (2025). Exploring the Influence of AI Adoption and Technological Readiness on Sustainable Performance in Pakistani Export Sector Manufacturing Small and Medium-Sized Enterprises. *Sustainability*, *17*(8), 3599. https://doi.org/10.3390/su17083599

Jebb, A. T., Ng, V., & Tay, L. (2021). A Review of Key Likert Scale Development Advances: 1995–2019. *Frontiers in Psychology*, *12*, 637547. https://doi.org/10.3389/fpsyg.2021.637547

Kishore, L., Pai, Y. P., & Shanbhag, P. (2024). Reliability and validity assessment of instrument to measure sustainability practices at shipping ports in India. *Discover Sustainability*, *5*(1), 236. https://doi.org/10.1007/s43621-024-00395-z

Koo, M., & Yang, S.-W. (2025). Likert-Type Scale. *Encyclopedia*, *5*(1), 18. https://doi.org/10.3390/encyclopedia5010018

Latupeirissa, J. J. P., Dewi, N. L. Y., Prayana, I. K. R., Srikandi, M. B., Ramadiansyah, S. A., & Pramana, I. B. G. A. Y. (2024). Transforming Public Service Delivery: A Comprehensive Review of Digitization Initiatives. *Sustainability*, *16*(7), 2818. https://doi.org/10.3390/su16072818

Lim, W. M., Khatri, P., Shiva, A., & Dabas, V. (2026). Guidelines for Scale Development and Validation. *Journal of Consumer Behaviour*, *25*(2), 953–973. https://doi.org/10.1002/cb.70096

Liu, F., Shao, Y., & Chen, M. (2026). Generative design strategies for additive manufacturing of lattice structures: A review. *Materials & Design*, *262*, 115431. https://doi.org/10.1016/j.matdes.2026.115431

Marović, I., Mandičák, T., Krajníková, K., Behúnová, A., & Mésároš, P. (2026). Artificial Intelligence and Building Information Modelling for Sustainable Construction Project Management and Digitalization in Construction. *Buildings*, *16*(4), 846. https://doi.org/10.3390/buildings16040846

Md Mizanur, R., & Datta, P. (2025). Data-driven business strategies with the power of the K-means algorithm. *International Journal of Higher Education Management*, *11*(02). https://doi.org/10.24052/IJHEM/V11N02/ART-1

Memon, M. A., Thurasamy, R., Ting, H., & Cheah, J.-H. (2024). PURPOSIVE SAMPLING: A REVIEW AND GUIDELINES FOR QUANTITATIVE RESEARCH. *Journal of Applied Structural Equation Modeling*, *9*(1), 1–23. https://doi.org/10.47263/JASEM.9(1)01

Mirindi, D., Mirindi, F., Bezabih, T., Sinkhonde, D., & Kiarie, W. (2025). Review: The Role of Artificial Intelligence in Building Information Modeling. *Proceedings of the 2025 Computers and People Research Conference*, 1–11. https://doi.org/10.1145/3716489.3728433

Moreno-Sánchez, P. A., Del Ser, J., Van Gils, M., & Hernesniemi, J. (2026). A design framework for operationalizing trustworthy artificial intelligence in healthcare: Requirements, tradeoffs and challenges for its clinical adoption. *Information Fusion*, *127*, 103812. https://doi.org/10.1016/j.inffus.2025.103812

Nguyen, T. H., Le, X. C., & Vu, T. H. L. (2022). An Extended Technology-Organization-Environment (TOE) Framework for Online Retailing Utilization in Digital Transformation: Empirical Evidence from Vietnam. *Journal of Open Innovation: Technology, Market, and Complexity*, *8*(4), 200. https://doi.org/10.3390/joitmc8040200

Nirmani, I. A. P. (2025). Barriers to digital participation in developing countries: Identifying technological, social, and cultural obstacles to community involvement. *GSC Advanced Research and Reviews*, *23*(2), 061–071. https://doi.org/10.30574/gscarr.2025.23.2.0130

Obeng, H. A., Gyamfi, B. A., Mensah, L., Arhinful, R., & Sarwar, A. (2026). Employees' behavioral intention to use AI and organizational efficiency in an emerging economy: The serial mediating roles of technology readiness and digital culture. *Discover Artificial Intelligence*, *6*(1), 251. https://doi.org/10.1007/s44163-026-01015-7

Okeke, A. (2023, December 9). *Anambra State Unveils 10,000 Low-Cost Housing Units in Isiagu*. Nigeria Housing Market. https://www.nigeriahousingmarket.com/news/anambra-state-unveils-10000-low-cost-housing-units-in-isiagu

Owolabi, D. J., Malagwi, D., Oyeyipo, O., & Ola-Ade, E. O. (2022). Application of artificial intelligence in the Nigerian building and construction industry. *International Journal of ADVANCED AND APPLIED SCIENCES*, *9*(10), 33–39. https://doi.org/10.21833/ijaas.2022.10.005

Peng, B., & Gao, S. (2025). Prediction of hospital length of stay: Leveraging ensemble tree models and intelligent feature selection. *Journal of Hospital Management and Health Policy*, *9*, 13–13. https://doi.org/10.21037/jhmhp-24-129

Sakita, B. M. (2026). Technological–inter-organizational–organizational–environmental (TIOE) framework for digital transformation of a maritime port in a developing country. *Research in Transportation Business & Management*, *67*, 101658. https://doi.org/10.1016/j.rtbm.2026.101658

Shaik, A. B., & Srinivasan, S. (2019). A Brief Survey on Random Forest Ensembles in Classification Model. In S. Bhattacharyya, A. E. Hassanien, D. Gupta, A. Khanna, & I. Pan (Eds.), *International Conference on Innovative Computing and Communications* (Vol. 56, pp. 253–260). Springer Singapore. https://doi.org/10.1007/978-981-13-2354-6_27

Tashakkori, A., Johnson, R. B., & Teddlie, C. (2021). *Foundations of Mixed Methods Research*. SAGE Publications, Inc. https://doi.org/10.4135/9781506350288

Tornatzky, L. G., Fleischer, M., & Chakrabarti, A. K. (1990). *The processes of technological innovation*. Lexington books.

Turok, I., Scheba, A., & Visagie, J. (2023). Rethinking urbanization and economic development: A synopsis. *Environment and Urbanization*, *35*(2), 297–309. https://doi.org/10.1177/09562478231193829

Uzochukwu, I. U., Gambo, N., & Nwoye, M. I. (2026a). Digital Technology Adoption: An Imperative for Performance Among Supervisory Agencies in the Nigerian Communications Sector. *European Journal of Business and Innovation Research*, *14*(2), 1–25. https://doi.org/10.37745/ejbir.2013/vol14n2125

Uzochukwu, I. U., Gambo, N., & Nwoye, M. I. (2026b). Digital Technology Adoption: An Imperative for Performance Among Supervisory Agencies in the Nigerian Communications Sector. *European Journal of Business and Innovation Research*, *14*(2), 1–25. https://doi.org/10.37745/ejbir.2013/vol14n2125

Wojtowicz, A., Paja, W., & Bentkowska, U. (2025). Feature Importance Ranking Using Interval-Valued Methods and Aggregation Functions for Machine Learning Applications. *Applied Sciences*, *15*(22), 12130. https://doi.org/10.3390/app152212130

Yang, L. (2025). AI-enhanced BIM Systems for Real-time Energy Performance Simulation. *Frontiers in Science and Engineering*, *5*(6), 29–43. https://doi.org/10.54691/1vre1d63

Yin, W. (2023). Does digital transformation matter to green innovation: Based on TOE framework and configuration perspective. *Environmental Science and Pollution Research*, *30*(44), 100046–100057. https://doi.org/10.1007/s11356-023-29438-0

Zhang, B., Yu, Y., Yi, S., Ding, Z., Yousefi, A. M., Li, J., & Lyu, X. (2025). Machine learning methods for compression capacity prediction and sensitivity analysis of concrete-filled steel tubular columns: State-of-the-art review. *Structures, 72,* 108259. https://doi.org/10.1016/j.istruc.2025.108259