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Determinants of Artificial Intelligence Adoption in Construction Project Delivery: Evidence from Large Construction Firms in Nigeria Using the TOE Framework

Sonter J. Chen^{1,*}, Aisha P. Abdullahi¹, Isaac A. John¹ and Precious A. Umoren²

¹Department of Architecture, Federal University of Technology, Minna, Nigeria

²Primetech Design and Engineering Nig. Ltd, Abuja, Nigeria

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*Corresponding Author

Email: sonterchen@gmail.com

ABSTRACT

Artificial intelligence (AI) is increasingly recognized as a transformative technology for enhancing construction project delivery. However, empirical evidence explaining the factors associated with its adoption remains limited, particularly in developing-country construction contexts. This study investigated the determinants of AI adoption across construction project delivery functions among large-scale construction firms in Nigeria using the Technology–Organization–Environment (TOE) framework. A quantitative survey design was adopted, and data were collected through a structured questionnaire administered to construction professionals across 14 purposively selected large-scale construction firms. A total of 288 valid responses were analyzed using IBM SPSS Statistics and SmartPLS 4. Descriptive statistics were employed to examine respondent characteristics, AI application areas, and construct performance, while Partial Least Squares Structural Equation Modelling (PLS-SEM) was used to test the hypothesized relationships. The findings indicate that AI adoption remains at a moderate stage, with implementation concentrated in design and BIM processes (50.7%) and planning and project control (38.9%). Organisational factors demonstrated the strongest statistical association with AI adoption ($\beta = 0.404$), followed by technological ($\beta = 0.169$) and environmental factors ($\beta = 0.158$), with the TOE model explaining 30.8% of the variance in adoption. The relatively high organisational readiness score alongside moderate AI adoption suggests that favourable internal conditions do not necessarily translate into extensive AI implementation. By providing TOE-based empirical evidence from these firms in Nigeria, the findings contribute to the growing literature on construction digitalization and offer practical insights for firms seeking to accelerate AI-enabled project delivery.

1. Introduction

In the built environment, artificial intelligence (AI) technologies are being integrated into activities that were traditionally dependent on expert judgement and manual coordination, including design optimisation, Building Information Modelling (BIM) coordination, cost estimation, scheduling, risk prediction, progress monitoring, quality management, and project decision support [1-2]. The growing application of AI across the Architecture, Engineering and Construction (AEC) industry has been documented through a scientometric research, which identifies optimisation, simulation, uncertainty, and project management among prominent research themes, while machine learning, neural networks, genetic algorithms, fuzzy logic, and fuzzy sets are among the most widely investigated AI approaches [3]. Recent advances in machine learning, computer vision, generative artificial intelligence, predictive analytics, and data-driven workflows have accelerated interest in AI as a mechanism for improving productivity, decision-making, risk management, and project delivery efficiency [4-7]. Recent Nigerian project-level evidence also demonstrates the application of BIM-enabled digital workflows in construction delivery [8].

The extent to which these technologies are adopted depends on technological, organisational, and environmental conditions that vary across firms and institutional contexts. Existing studies further suggest that implementation depends not only on technological availability but also on organizational readiness and external conditions such as leadership support, digital capability, financial capacity, and institutional pressures [9-12]. Recent evidence also suggests that barriers to AI implementation extend beyond technical limitations to organisational capability, governance, workforce skills, data quality, and contextual conditions [13]. These challenges may be particularly pronounced in developing construction contexts, where capability, digital maturity, infrastructure readiness, and institutional conditions can constrain technology implementation [14]. The Technology–Organization–Environment (TOE) framework provides an established theoretical basis for explaining organisational technology adoption. Originally developed by Tornatzky *et al.* [15], the framework conceptualises adoption through technological, organisational, and environmental contexts.

In Nigeria, despite growing use of digital technologies among large-scale construction firms, empirical evidence explaining AI adoption across project delivery remains limited. Existing studies have primarily examined awareness, barriers, and opportunities rather than empirically modelling the technological, organisational, and environmental conditions associated with adoption [11, 16]. Recent Nigerian evidence has also examined AI adoption among construction small and medium-sized enterprises (SMEs), identifying technological infrastructure readiness as a prominent predictor of adoption [17]. Against this background, this study examines the association between technological, organisational, and environmental conditions and AI adoption across project delivery functions among large-scale construction firms in Nigeria using the TOE framework.

1.1. Aim and Objectives

To examine the factors associated with artificial intelligence adoption across construction project delivery functions among large-scale construction firms in Nigeria using the TOE framework. The objectives are;

1. To identify the current areas and extent of artificial intelligence application across construction project delivery functions among large-scale construction firms in Nigeria.
2. To examine the technological, organisational, and environmental factors associated with artificial intelligence adoption among large-scale construction firms in Nigeria.
3. To assess the relationships between technological, organisational, and environmental factors and AI adoption across project delivery functions among large-scale construction firms in Nigeria.

2. Literature Review

2.1. AI Applications Across Construction Project Delivery Functions

At the broader AEC level, a scientometric analysis of 41,827 Scopus records identified optimisation, simulation, uncertainty, and project management as among the most prominent topics addressed through AI, demonstrating

the broad application of AI methods across construction-related research [3]. Existing evidence suggests that AI implementation does not occur uniformly across construction organisations but develops selectively in functions characterised by intensive information processing, coordination complexity, and repetitive decision environments [1, 6, 9, 18]. Among project delivery functions, design and BIM environments currently demonstrate some of the highest levels of AI implementation. Studies report increasing use of AI-enabled generative design, automated design assessment, optimisation algorithms, BIM coordination, and intelligent decision support, transforming design workflows from conventional modelling toward predictive and data-driven processes [1, 6, 9].

Implementation has similarly expanded into planning and project control functions. Machine learning and predictive analytics are increasingly applied for scheduling, forecasting, resource optimisation, productivity prediction, cost estimation, and project performance monitoring [19]. Recent studies indicate that planning and control remain among the most dominant implementation domains because these functions generate structured project information suitable for algorithmic learning and optimization [20, 21, 7]. At execution stages, AI implementation has expanded into site monitoring and operational management through computer vision, automated reporting, progress tracking, image recognition, quality assessment, and predictive decision-support systems [22]. Implementation tends to be strongest in data-rich activities that support continuous learning and optimization [9, 23, 24]. Although these studies demonstrate the expanding range of AI applications in construction, much of the literature remains application-oriented, focusing on specific technologies or project functions.

2.2. Technology–Organization–Environment (TOE) Framework

The TOE framework established by Tornatzky *et al.* [15] explains organisational technology adoption through three interacting dimensions, technological context, organisational context, and environmental context. Recent AI adoption studies demonstrate its applicability across complex organisational settings, including construction, where TOE-based modelling has identified facilitating conditions and competitive pressure as important factors associated with AI use [25-27].

The technological context captures characteristics associated with the technology itself and organisational readiness for implementation. Existing literature identifies perceived usefulness, compatibility, data availability, system interoperability, digital infrastructure, and implementation complexity as recurring technological determinants of AI adoption [28-30]. The organisational context concerns the internal capabilities required for implementation, including leadership support, financial readiness, employee competence, organisational learning, and innovation orientation. The environmental context captures external conditions that shape organisational adoption decisions, including competitive pressure, client expectations, policy support, access to technical ecosystems, and industry norms [11]. Recent evidence from Sub-Saharan African construction markets further indicates that infrastructure limitations, skills deficits, regulatory uncertainty, and institutional challenges can constrain AI adoption [31]. Evidence from Industry 4.0 adoption in construction similarly indicates that successful implementation requires attention to both technological and human capabilities [32].

Despite its broad applicability, TOE does not prescribe a fixed set of determinants within each context. Its flexibility enables researchers to adapt the framework to specific technologies and institutional settings, but this flexibility can also result in inconsistent operationalisation across studies. The relative importance of the three contexts may therefore vary according to the technology, industry, organisational characteristics, and institutional environment. This study treats TOE as an organising explanatory framework rather than a comprehensive representation of all possible determinants of AI adoption in the AEC industry.

Evidence from Nigerian AEC firms further supports this multidimensional perspective and recent studies argue that AI implementation requires organisational adaptation extending beyond technology acquisition into changes in governance, workflows, and capability development [33-35]. Using survey-based modelling in a developing-economy construction context, Dosumu *et al.* [36] identified organisational preparedness, knowledge conditions, and technological readiness as critical factors associated with AI implementation outcomes, reinforcing the explanatory relevance of organisational adoption frameworks. Babatunde *et al.* [37], identified 20 barriers to BIM implementation in Nigerian AEC firms and grouped them into three major factors: weak top-management support

and BIM-environment issues; the cost of BIM software and training; and incompatibility, legal, contractual, and cultural issues.

2.3. Conceptualising AI Adoption

A recurring methodological issue within AI adoption research concerns how adoption is conceptualised and measured. Existing studies frequently operationalise adoption as a binary outcome or assess implementation solely in terms of technology availability despite increasing evidence that organisational adoption develops progressively and unevenly across operational functions and implementation stages [11, 34]. Recent literature increasingly conceptualises adoption as organisational capability reflected through implementation intensity, strategic integration, operational embedding, and future expansion readiness [20, 24, 25]. Within construction environments, this perspective suggests that adoption should not be understood merely as whether firms possess AI tools but rather whether AI becomes integrated into routine project delivery activities. On this note, the study conceptualises AI adoption as the extent to which construction firms integrate AI-enabled practices across project delivery functions and develop readiness for broader implementation.

2.4. Research Gap

Despite growing interest in AI within construction research, important gaps remain. First, existing studies tend to focus on specific AI technologies, providing limited understanding of AI adoption as an integrated organisational process [1, 9]. Second, Nigerian research has largely examined awareness, barriers, opportunities, and readiness rather than empirically modelling the technological, organisational, and environmental conditions associated with AI adoption [11, 38]. Third, empirical evidence from developing construction contexts remains relatively limited despite differences in organisational capability, digital maturity, and institutional environments [14]. Accordingly, the present study addresses these gaps by examining both the current distribution of AI applications across project delivery functions and the association between technological, organisational, and environmental conditions and AI adoption among large construction firms in Nigeria.

2.5. Research Hypothesis

Drawing on the TOE framework, this study proposes that technological, organisational, and environmental conditions are positively associated with AI adoption across project delivery functions among large construction firms and the following hypotheses were therefore proposed:

H1: Technological factors are positively associated with AI adoption across project delivery functions among large construction firms.

H2: Organisational factors are positively associated with AI adoption across project delivery functions among large construction firms.

H3: Environmental factors are positively associated with AI adoption across project delivery functions among large construction firms.

3. Research Methods

3.1. Research Design and Analytical Framework

This study adopts a quantitative cross-sectional survey design to examine the associations between technological, organisational, and environmental conditions and AI adoption across construction project delivery functions among large-scale construction firms in Nigeria. This approach was considered appropriate for assessing the prevailing conditions of AI adoption and the relationships between the study constructs. However, because data were collected at one point in time, the design does not permit temporal or causal inference. In the proposed model, technological, organisational, and environmental contexts are specified as predictor constructs, while AI adoption across construction project delivery functions is specified as the endogenous construct.

The analytical framework was derived from the TOE framework. Technology, Organisation, and Environment were specified as predictor constructs, while AI Adoption was specified as the outcome construct. The framework provided the basis for testing H1, H2, and H3, as shown in Fig. (1).

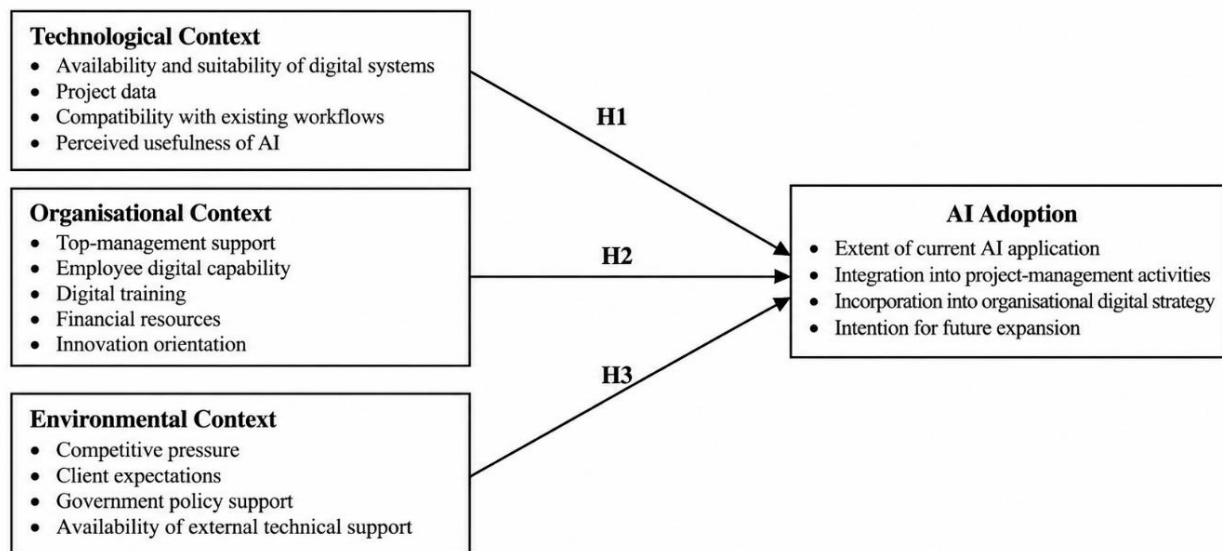


Figure 1: Analytical framework for AI adoption using the TOE framework.

3.2. Study Population and Firm Selection

Large-scale construction firms in Nigeria were considered appropriate for the investigation and were selected based on predefined eligibility criteria: (i) sustained construction operations in Nigeria; (ii) involvement in large-scale building, civil infrastructure, or industrial projects; (iii) established multidisciplinary project-delivery structures; (iv) recognised presence within the Nigerian construction industry; and (v) evidence of the use of digital construction practices in project delivery. Table 1 provides an overview of the participating construction firms and the respondents included in the study, establishing the organisational context of the sampled firms.

Table 1: Characteristics of participating construction firms.

S/N	Firm	Location	Primary Project Sectors	Classification	Years of Operation	Respondents (n)
1	Julius Berger Nigeria Plc	Abuja	Building, roads, bridges, industrial infrastructure	Multinational	56	28
2	Dantata & Sawoe Construction Co. Ltd.	Abuja	Roads, bridges, buildings, infrastructure	Indigenous	50	27
3	Setraco Nigeria Ltd.	Abuja	Roads, bridges, highways, civil infrastructure	Multinational	49	25
4	China Civil Engineering Construction Corporation (CCECC Nigeria)	Abuja	Railways, roads, bridges, airports, infrastructure	Multinational	45	35
5	Arab Contractors (Nigeria) Ltd.	Abuja	Buildings, roads, bridges, water infrastructure	Multinational	35	25
6	ITB Nigeria Ltd.	Lagos	Residential, commercial, institutional, EPC	Multinational	31	18
7	Cappa & D'Alberto Plc	Lagos	Commercial, residential, institutional, high-rise buildings	Indigenous	94	10

Table 1 (contd....)

S/N	Firm	Location	Primary Project Sectors	Classification	Years of Operation	Respondents (n)
8	Elalan Construction Company Ltd.	Lagos	Residential, commercial, industrial, civil engineering	Multinational	44	14
9	Costain West Africa Plc	Lagos	Building, civil engineering, infrastructure	Multinational	78	12
10	Hitech Construction Company Ltd.	Lagos	Roads, bridges, highways, civil engineering	Indigenous	38	23
11	Arbico Plc	Lagos	Building, design-and-build, infrastructure, project management	Indigenous	68	12
12	Reynolds Construction Company (RCC)	Abuja	Roads, bridges, buildings, water engineering	Multinational	58	25
13	Monier Construction Company (MCC)	Port Harcourt	Roads, bridges, buildings, civil engineering	Indigenous	71	20
14	Saipem Nigeria Ltd.	Port Harcourt	Oil & gas, EPC, industrial, offshore/marine infrastructure	Multinational	60	14
Total	14 firms	3 locations	—	—	—	288

Note: Some of the participating firms operate across multiple locations in Nigeria. The location reported in this table indicates the location from which relevant firm-level information was obtained and should not be interpreted as indicating that the firm's operations are restricted to that location. Years of operation are reported based on the firms' established dates and the study reference year 2026.

3.3. Sampling Technique

At the organisational level, purposive sampling was used to select the 14 large-scale construction firms based on the predefined eligibility criteria described in Section 3.2. At the respondent level, purposive and snowball sampling techniques were employed to identify eligible construction professionals within the participating firms. Respondent eligibility was restricted to professionals directly involved in construction project delivery and sufficiently familiar with the digital practices of their organisations.

Initial respondents were reached through established organisational contacts and professional networks. Eligible participants were subsequently encouraged to circulate the questionnaire among other qualified professionals within their organisations and professional networks, thereby introducing a snowball component to the recruitment process. Because questionnaire circulation occurred through multiple organisational contacts and professional networks without a centrally controlled sampling frame, the total number of professionals who received or accessed the questionnaire could not be reliably established. Consequently, a conventional questionnaire response rate could not be calculated. Following screening for eligibility and completeness, 288 valid responses were retained for analysis.

3.4. Data Sources and Data Collection Procedure

The study relied primarily on cross-sectional primary survey data collected from eligible construction professionals within the 14 participating firms. Primary data were collected from construction professionals directly involved in project delivery, including architects, engineers, builders, quantity surveyors, project managers, and BIM specialists. A structured questionnaire was administered electronically through Google Forms.

The questionnaire comprised five sections covering respondent characteristics and AI applications (A), technological factors (B), organisational factors (C), environmental factors (D), and AI adoption (E). Construct items were measured using a five-point Likert scale ranging from 1 = strongly disagree to 5 = strongly agree. Following data collection and screening, a total of 288 valid responses were obtained, exceeding the study's initial target of 180–250 responses [39].

3.5. Data Analysis and Hypothesis Testing

Data were analysed using IBM SPSS Statistics and SmartPLS 4. The analytical procedure was conducted in sequential stages. First, descriptive statistics, including frequencies, percentages, means, and standard deviations, were used to profile respondents, determine current areas of AI application, and assess perceptions of the TOE and AI-adoption constructs.

Second, the measurement model was evaluated before testing the hypothesised structural relationships. Internal consistency reliability was assessed using Cronbach's alpha and Composite Reliability (CR), while convergent validity was examined using indicator loadings and Average Variance Extracted (AVE). Discriminant validity was evaluated using the Fornell–Larcker criterion and heterotrait–monotrait ratio (HTMT). Because the predictor and outcome variables were collected through the same self-administered questionnaire, Harman's single-factor test was additionally conducted as a diagnostic assessment of potential common method bias.

Third, Partial Least Squares Structural Equation Modelling (PLS-SEM) was employed to test the hypothesised relationships between the three TOE dimensions and AI adoption. Structural-model assessment included standardised path coefficients (β), bootstrapped t-statistics and p-values, coefficient of determination (R^2), effect sizes (f^2), and Variance Inflation Factor (VIF). H1 tested the relationship between Technology and AI Adoption, H2 examined the relationship between Organisation and AI Adoption, and H3 assessed the relationship between Environment and AI Adoption. Statistical significance was assessed at $p < 0.05$. Given the cross-sectional design, statistically significant paths were interpreted as predictive associations rather than causal effects.

As an exploratory extension of the main structural model, pairwise interaction terms among the TOE dimensions were also examined to assess whether the association between one TOE context and AI adoption varied according to another TOE context. The interaction terms Organisation $\times$ Technology, Organisation $\times$ Environment, and Technology $\times$ Environment were estimated while controlling for the corresponding main effects

4. Results

The results are presented in five stages. First, respondent characteristics and current areas of AI application across project delivery functions are examined. Second, descriptive statistics are used to assess perceptions of technological, organisational, environmental, and AI adoption conditions. Third, the measurement properties of the constructs are assessed through indicator loadings, internal consistency, convergent validity, and discriminant validity. Fourth, common method bias is examined. Finally, the structural relationships between the TOE dimensions and AI adoption are evaluated, followed by discussion of the findings and practical implications.

4.1. Respondent Characteristics and Current Areas of AI Applications in Participating Firms

As shown in Table 2 below, the respondent pool was dominated by Engineers (38.2%) and Architects (21.5%), indicating strong representation from technical and project delivery professions. Respondents were relatively distributed across experience levels, although professionals with 6–10 years (27.4%) and 11–15 years (26.7%) constituted the largest groups. Regarding reported level of AI use, moderate AI use (34.7%) was the most frequently reported, followed by low and high levels of use, indicating that reported AI use was predominantly at low-to-moderate levels. Firms were also characterised by diverse project portfolios, with the largest proportion delivering projects across building, road, bridge, and industrial sectors (30.6%), reflecting broad project delivery exposure. Concerning current implementation areas, AI application was concentrated predominantly in design and BIM processes (50.7%) and planning and project control (38.9%), while comparatively lower adoption was observed in commercial management, procurement, and decision-support functions, indicating uneven integration of AI across project delivery activities.

Table 2: Respondent characteristics and current ai applications in the firms (n = 288).

Variable	Response Category	Frequency	Percentage (%)
A1. Profession	Engineer	110	38.2
	Architect	62	21.5
	Project Manager	51	17.7
	Quantity Surveyor	37	12.8
	Builder	15	5.2
	BIM Specialist	13	4.5
A2. Professional Experience	6–10 years	79	27.4
	11–15 years	77	26.7
	1–5 years	71	24.7
	16 years and above	61	21.2
A3. Current Level of AI Use in the Firm	Moderate	100	34.7
	Low	82	28.5
	High	59	20.5
	None	47	16.3
A4. Project Category	Building + Road + Bridge + Industrial	88	30.6
	Building Construction	70	24.3
	Road + Bridge + Industrial	37	12.8
	Building + Road	27	9.4
	Building + Road + Bridge	23	8.0
	Others	43	14.9
A5. Current Areas of AI Application in the Firm	Design and BIM processes	146	50.7
	Planning and project control	112	38.9
	No current AI application	46	16.0
	Site operations and monitoring	36	12.5
	Decision support and analytics	22	7.6
	Cost and commercial management	17	5.9
	Procurement and supply chain management	17	5.9

Note: A5 was a multiple-response item; percentages therefore do not sum to 100%.

4.2. Descriptive Statistics of TOE Constructs

The descriptive results indicate variation across the three TOE contexts (Table 3). Organisational conditions recorded the highest composite mean (3.54), whereas technological (3.22) and environmental (3.12) conditions were moderate. AI adoption recorded a moderate mean of 3.13. The difference between the relatively high organisational score (3.54) and the moderate AI adoption score (3.13) indicates that favourable organisational conditions coexist with only moderate reported AI adoption. At the indicator level, organisational innovation orientation recorded the highest mean (4.21), followed by client expectations for digital project delivery (3.96), employee digital capability (3.67), and perceived usefulness of AI (3.60). In contrast, compatibility with existing project workflows recorded a mean of 2.74, government policy support recorded the lowest environmental mean (2.35), and external technical support recorded a mean of 2.72. For AI adoption, the intention to expand AI use in future projects recorded the highest mean (3.31), while integration into project management activities recorded the lowest (2.91).

Table 3: TOE constructs on AI adoption (n = 288).

Construct	Indicator	Mean	SD	Rank	Interpretation
Technology	Existing digital systems support AI adoption	3.26	1.23	3	Moderate
	Our organization has access to sufficient project data for AI applications	3.28	1.28	2	Moderate
	AI tools are compatible with existing project delivery workflows	2.74	1.25	4	Moderate
	AI technologies are perceived as useful for improving project performance	3.60	1.37	1	High
T - Composite		3.22	1.32	-	Moderate
Organization	Top management supports AI implementation	3.07	1.09	5	Moderate
	Employees possess adequate digital capability	3.67	1.12	2	High
	Our organization invests in digital training	3.42	1.24	3	High
	Financial resources are available for AI implementation	3.35	1.29	4	Moderate
	Our organization encourages innovation in project delivery	4.21	0.78	1	Very High
O - Composite		3.54	1.18	-	High
Environment	Competitive pressure encourages AI adoption	3.43	1.32	2	High
	Clients increasingly expect digital project delivery	3.96	0.93	1	High
	Government policies support AI implementation	2.35	1.29	4	Low
	External technical support for AI adoption is available	2.72	1.20	3	Moderate
E-Composite		3.12	1.35	—	Moderate
AI Adoption	Our organization actively applies AI in construction project delivery	3.25	1.10	2	Moderate
	AI is increasingly integrated into project management activities	2.91	1.18	4	Moderate
	AI implementation forms part of our organization's digital strategy	3.05	1.30	3	Moderate
	Our organization plans to expand AI use in future projects	3.31	1.17	1	Moderate
AD- Composite		3.13	1.20	-	Moderate

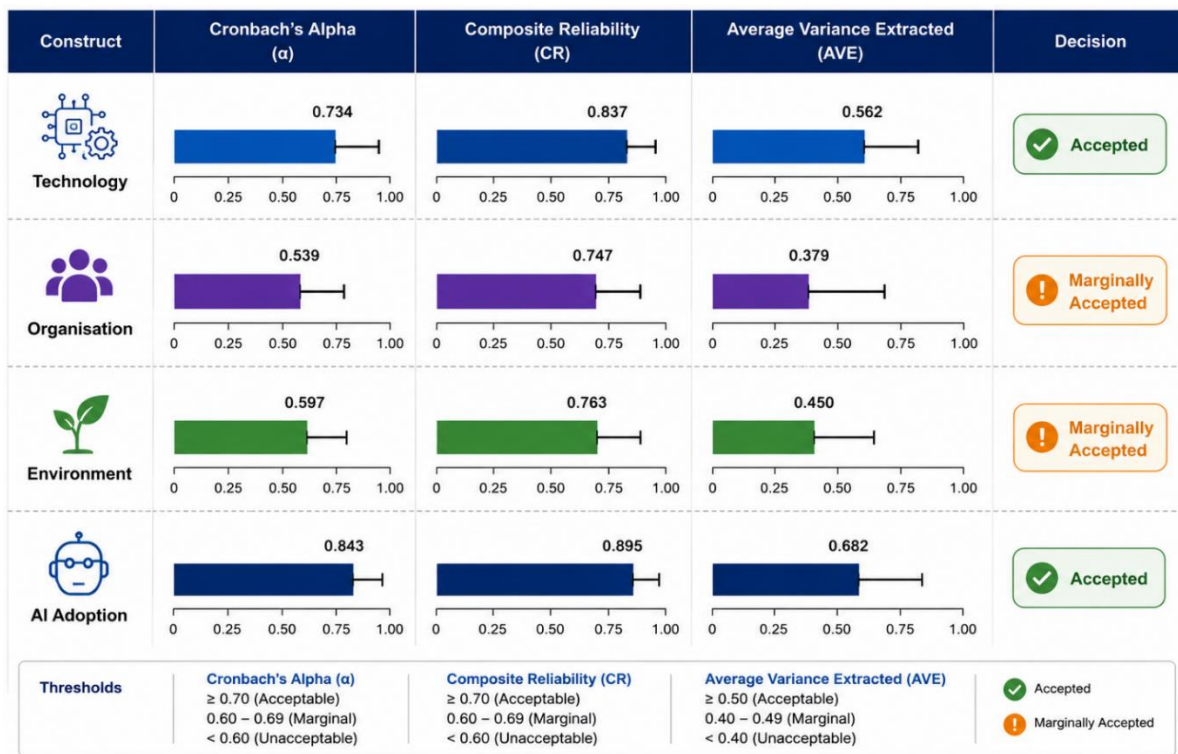
4.3. Assessment of the Relationships between TOE Factors and AI Adoption

This section presents the measurement and structural model results used to assess the relationships between TOE factors on AI adoption across project delivery functions. Reliability and validity analysis were first conducted to assess the measurement model, after which PLS-SEM was applied to estimate relationships and evaluate the explanatory capability of the TOE framework within the study context.

4.3.1. Measurement Model Assessment

Internal consistency was assessed using Cronbach's alpha (α) and Composite Reliability (CR), while convergent validity was evaluated using Average Variance Extracted (AVE). Fig. (2) presents the construct-level reliability and convergent validity results for Technology, Organisation, Environment, and AI Adoption, including their respective α , CR, and AVE values and the corresponding assessment against the stated threshold criteria. Table 4 presents the individual indicator loadings for all four constructs and identifies the assessment of each indicator against the 0.70 loading threshold.

The measurement model was assessed using the 288 valid observations and 17 indicators. Technology recorded acceptable internal consistency (Cronbach's $\alpha = 0.734$; CR = 0.837) and convergent validity (AVE = 0.562), with indicator loadings ranging from 0.718 to 0.806. AI Adoption similarly demonstrated strong internal consistency ($\alpha = 0.843$; CR = 0.895) and convergent validity (AVE = 0.682), with loadings ranging from 0.776 to 0.883.



Note: Values represent construct reliability and convergent validity assessment.

Figure 2: Construct reliability and convergent validity assessment.

Table 4: Indicator loadings and assessment.

Construct	Indicator	Loading	Assessment
Technology	T1	0.806	Acceptable loading
	T2	0.735	Acceptable loading
	T3	0.734	Acceptable loading
	T4	0.718	Acceptable loading
Organisation	O1	0.456	Lower loading; retained
	O2	0.523	Lower loading; retained
	O3	0.683	Lower loading; retained
	O4	0.732	Acceptable loading
	O5	0.643	Lower loading; retained
Environment	E1	0.803	Acceptable loading
	E2	0.580	Lower loading; retained
	E3	0.612	Lower loading; retained
	E4	0.669	Lower loading; retained
AI Adoption	AD1	0.776	Acceptable loading
	AD2	0.883	Acceptable loading
	AD3	0.847	Acceptable loading
	AD4	0.776	Acceptable loading

Organisation recorded Cronbach's $\alpha = 0.539$, CR = 0.747, and AVE = 0.379, with indicator loadings ranging from 0.456 to 0.732. Environment recorded $\alpha = 0.597$, CR = 0.763, and AVE = 0.450, with loadings ranging from 0.580 to 0.803. Both constructs therefore fall below the conventional AVE threshold of 0.50, indicating that convergent validity is not fully established under the current reflective specification. Several indicators also recorded loadings below 0.70, particularly within Organisation and Environment. Organisation and Environment should not be described as demonstrating fully satisfactory convergent validity. Their structural relationships with AI adoption are therefore interpreted with appropriate caution, and these measurement limitations are considered when discussing the structural-model findings. Indicators with loadings below 0.70 were retained where their removal was not considered theoretically justified and where the indicators remained relevant to the intended construct domain. Nevertheless, the resulting AVE values for Organisation and Environment indicate that convergent validity is not fully established, and the associated structural relationships are therefore interpreted cautiously.

4.3.2. Discriminant Validity

Discriminant validity was assessed using the Fornell–Larcker criterion and the heterotrait–monotrait ratio (HTMT) to determine whether the study constructs were empirically distinct from one another as presented in Table 5.

Table 5: Discriminant validity: Fornell–Larcker criterion and HTMT.

Construct	Technology	Organisation	Environment	AI Adoption
Panel A: Fornell–Larcker Criterion				
Technology	0.749	0.658	0.608	0.522
Organisation	0.658	0.615	0.094	0.754
Environment	0.608	0.094	0.671	0.478
AI Adoption	0.522	0.754	0.478	0.826
Panel B: HTMT				
Technology	1.000	0.658	0.938	0.522
Organisation	0.658	1.000	0.577	0.754
Environment	0.938	0.577	1.000	0.478
AI Adoption	0.522	0.754	0.478	1.000

The Fornell–Larcker results indicate satisfactory discriminant validity for most construct relationships; however, a concern is observed between Organisation and AI Adoption, where the Organisation square root of AVE (0.615) is lower than its correlation with AI Adoption (0.754). The HTMT results similarly identify a potential discriminant-validity concern between Technology and Environment, with an HTMT value of 0.938 exceeding the 0.90 threshold. The remaining HTMT values are below 0.90. These results suggest that, although most constructs demonstrate adequate empirical separation, Organisation–AI Adoption and particularly Technology–Environment exhibit some degree of construct overlap.

4.3.3. Common Method Bias

Because the study collected both predictor and outcome measures using a self-administered questionnaire, common method bias was assessed using Harman's single-factor test. The analysis included the 17 measurement items. The first unrotated factor accounted for 31.62% of the total variance, which is below the conventional 50% threshold. The result therefore does not indicate that a single factor accounts for the majority of covariance among the measurement items. Nevertheless, Harman's test is only a diagnostic rather than definitive evidence that common method bias is absent, and the possibility of residual method effects cannot be completely excluded.

4.3.4. Structural Model Assessment and Hypothesis Testing

Following assessment of the measurement model, the structural model was estimated using PLS-SEM to examine the associations between technological, organisational, and environmental conditions and AI adoption across project delivery functions, as shown in Table 6.

Table 6: Structural model results and hypothesis testing.

Hypothesis	Structural Path	β	Bootstrap t	p-value*	f^2	VIF	Decision
H1	Technology → AI Adoption	0.169	2.592	0.010	0.021	1.951	Supported
H2	Organisation → AI Adoption	0.404	8.618	<0.001	0.189	1.249	Supported
H3	Environment → AI Adoption	0.158	2.099	0.036	0.022	1.663	Supported

The structural model explained 30.8% of the variance in AI adoption ($R^2 = 0.308$; adjusted $R^2 = 0.301$). All three hypothesised relationships were positive and statistically significant. Technology was positively associated with AI adoption ($\beta = 0.169$, bootstrap $t = 2.592$), supporting H1. Organisation demonstrated the strongest positive association with AI adoption ($\beta = 0.404$, bootstrap $t = 8.618$), supporting H2, while Environment showed a smaller but significant positive association ($\beta = 0.158$, bootstrap $t = 2.099$), supporting H3. The effect size was small for Technology ($f^2 = 0.021$) and Environment ($f^2 = 0.022$), whereas Organisation demonstrated a larger effect ($f^2 = 0.189$). VIF values ranged from 1.249 to 1.951, indicating no problematic multicollinearity. Given the cross-sectional design, these relationships are interpreted as statistical associations rather than causal effects.

4.3.5. Exploratory Interaction Analysis

To further examine whether the relationships among the TOE dimensions operate conditionally, three pairwise interaction terms were tested: Organisation × Technology, Organisation × Environment, and Technology × Environment. Each interaction was assessed while controlling for the corresponding main effects. The results are presented in Table 7.

Table 7: Interaction effects among TOE contexts on AI adoption.

Interaction Term	β	t-Value	p-Value	Decision
Organisation × Technology → AI Adoption	0.012	0.207	0.836	Not significant
Organisation × Environment → AI Adoption	-0.172	-3.747	<0.001	Significant
Technology × Environment → AI Adoption	-0.321	-7.645	<0.001	Significant

Note: β = standardised interaction coefficient. Statistical significance was assessed at $p < 0.05$.

The interaction analysis produced mixed results. The Organisation × Technology interaction was positive but statistically insignificant ($\beta = 0.012$, $t = 0.207$, $p = 0.836$), indicating no evidence that the association between organisational conditions and AI adoption varies systematically with technological conditions. In contrast, the Organisation × Environment interaction was negative and statistically significant ($\beta = -0.172$, $t = -3.747$, $p < 0.001$), indicating that the association between organisational conditions and AI adoption varies according to environmental conditions. Similarly, the Technology × Environment interaction was negative and statistically significant ($\beta = -0.321$, $t = -7.645$, $p < 0.001$), suggesting that the relationship between technological conditions and AI adoption varies across levels of environmental conditions.

These interaction effects provide additional evidence that the TOE dimensions may not operate entirely independently in explaining AI adoption. In particular, the significant interaction involving Environment suggests that the effect of internal technological and organisational conditions may depend partly on the external context in which construction firms operate. However, because the study is cross-sectional, these interaction effects are interpreted as conditional associations rather than causal effects.

4.4. Discussion of Findings

The findings provide empirical evidence that AI adoption across project delivery functions among large-scale construction firms in Nigeria remains moderate, functionally uneven, and more strongly associated with organisational conditions than with technological or environmental conditions.

4.4.1. Functional Pattern and Maturity of AI Adoption

The concentration of AI application in design and BIM (50.7%) and planning and project control (38.9%) indicates that adoption within Nigerian large-scale construction firms is function-specific rather than uniformly distributed across the project-delivery lifecycle. This pattern aligns with international evidence suggesting that Construction AI implementation tends to emerge first in project functions characterised by intensive information exchange, coordination complexity, repetitive decision processes, and availability of structured digital datasets, particularly within design, BIM-enabled coordination, planning, and monitoring activities [40-42].

Studies [1, 9, 20] similarly identify design optimisation, BIM-enabled coordination, project planning, monitoring and predictive decision-support as prominent areas of construction AI application. The present findings therefore reinforce the view that AI adoption develops incrementally across project functions rather than uniformly across organisations. However, compared with evidence from developed construction economies where AI deployment is increasingly extending toward autonomous construction operations and integrated decision systems [44] and [45], the Nigerian firms in this study remain more concentrated in functions with established digital workflows and structured project information.

The moderate level of organisational AI use reported by respondents further suggests that implementation remains in a transitional stage rather than full operational institutionalization. This finding is consistent with [36], who reported that implementation intensity in developing construction environments is constrained less by awareness and more by organisational and capability readiness conditions. The similarity between both studies suggests that construction firms in emerging economies may possess growing interest in AI while still lacking the institutional and organisational maturity required for large-scale operational deployment. Felemban *et al.* [11] reported that readiness factors, rather than technological availability alone, largely determine implementation outcomes in construction environments. Similarly, Dwivedi *et al.* [34] argued that successful AI implementation requires organisational adaptation beyond acquisition of digital tools. The current findings extend this argument by demonstrating that Nigerian construction firms exhibit moderate implementation intensity despite relatively favourable perceptions toward future expansion of AI use.

4.4.2. Organisational Readiness and AI Adoption

The organisational context demonstrated the strongest association with AI adoption, recording the highest composite mean (3.54) and the strongest structural effect ($\beta = 0.404$, $p < 0.001$; $f^2 = 0.189$), compared with Technology ($\beta = 0.169$, $p = 0.010$; $f^2 = 0.021$) and Environment ($\beta = 0.158$, $p = 0.036$; $f^2 = 0.022$). This indicates that, among the sampled large-scale construction firms, internal organisational conditions are more strongly associated with AI adoption than technological or environmental conditions. The finding supports the organisational dimension of the TOE framework and is consistent with evidence that organisational readiness, management support, workforce capability, and internal preparedness are important determinants of AI adoption [11, 12, 36].

The indicator-level results provide further explanation for this finding. Innovation orientation recorded the highest organisational mean (4.21), followed by employee digital capability (3.67) and investment in digital training (3.42), indicating relatively favourable internal conditions for digital transformation. However, top-management support recorded a lower mean (3.07), suggesting that organisational willingness to innovate may not always be matched by equivalent executive commitment to AI implementation. This is consistent with evidence that management commitment, organisational capability, and preparedness influence the transition from technological interest to implementation [11, 12]. The relatively stronger organisational effect suggests that AI adoption depends not only on technology availability but also on firms' capacity to absorb, integrate, and sustain its use. While innovation orientation and workforce preparedness indicate favourable conditions for digital transformation, comparatively weaker management commitment may limit the translation of this readiness into

sustained AI implementation. This may help explain the stronger organisational association with AI adoption despite the overall moderate level of implementation.

The finding also aligns with the broader argument that AI adoption requires organisational adaptation beyond technology acquisition, including changes in capabilities, governance, workflows, and management practices [34]. In the Nigerian AEC context [37] similarly identified weak top-management support, training and software costs, organisational and cultural conditions as barriers to BIM implementation, reinforcing the importance of internal organisational capacity for digital technology adoption. Overall, the results suggest a readiness–implementation gap: firms demonstrate favourable organisational conditions and strong innovation orientation, yet overall, AI adoption remains moderate. Organisational readiness therefore appears to be an important mechanism through which technological opportunities are translated into broader AI implementation across project-delivery functions.

4.4.3. Technological Conditions and AI Adoption

Technological conditions were positively associated with AI adoption ($\beta = 0.169$, $p = 0.010$), supporting H1, although the effect size was small ($f^2 = 0.021$). This indicates that technological conditions contribute to AI adoption, but their influence is weaker than that of organisational conditions. The small effect size is particularly informative because it indicates that technological conditions, although statistically significant, have limited practical explanatory strength within the model. In other words, the presence of digital systems, project data, and favourable perceptions of AI does not necessarily translate into substantial increases in AI adoption when these technologies are not readily compatible with existing project-delivery workflows.

The descriptive results provide further explanation. Respondents reported relatively favourable perceptions of AI usefulness (Mean = 3.60) and moderate access to project data (3.28) and existing digital systems (3.26). However, compatibility between AI tools and existing project-delivery workflows recorded a lower mean (2.74). The difference between perceived usefulness and workflow compatibility is therefore significant to the interpretation of H1. Respondents appear to recognise the value of AI, but the comparatively lower compatibility rating points to a potential implementation constraint at the interface between AI tools and existing project systems and processes. This suggests that the key technological challenge is not simply recognising the value of AI but integrating it with existing systems and workflows. This finding is consistent with construction research identifying compatibility, facilitating conditions, data availability, and existing digital infrastructure as important determinants and barriers to AI implementation [19, 20, 27, 41]. These findings support H1 while indicating that technological conditions constitute a necessary but comparatively limited component of AI adoption within the sampled firms. The results suggest that improving digital infrastructure without addressing interoperability and workflow integration may not be sufficient to achieve broader AI implementation.

4.4.4. Environmental Conditions and AI Adoption

Environmental conditions were positively associated with AI adoption ($\beta = 0.158$, $p = 0.036$), supporting H3, although the effect size was small ($f^2 = 0.022$). The environmental context was also differentiated at the descriptive level: client expectations for digital project delivery recorded a relatively high mean (3.96) and competitive pressure 3.43, whereas government policy support was substantially lower (2.35) and external technical support recorded 2.72. This pattern suggests that market pressures are providing stronger incentives for AI adoption than the wider institutional environment. The relatively small effect size suggests, however, that these external pressures have limited practical explanatory strength when compared with organisational conditions. High client expectations may create incentives for firms to improve their digital capabilities, but incentives alone may not be sufficient to produce sustained AI implementation where policy support and external technical assistance remain comparatively weak. Thus, the environmental context appears to influence the adoption environment without necessarily providing all the institutional conditions required for firms to move from digital responsiveness to systematic AI integration. The finding is consistent with research identifying regulatory conditions, institutional support, technical capability, skills, and market pressures as important factors shaping AI adoption in developing construction contexts [30, 35, 36].

This distinction is important for interpreting H3 within the TOE framework. The environmental context does not operate as a uniformly supportive external condition; rather, its components exert different forms of influence.

Market-facing factors such as client expectations and competitive pressure may create demand for technological improvement, whereas policy support and technical assistance can provide the institutional and technical capacity needed to respond to that demand. The coexistence of relatively stronger market pressure and weaker institutional support therefore provides a plausible explanation for the significant but small association between environmental conditions and AI adoption observed in this study. For the Nigerian construction sector, the implication is that clients and competitive pressures may be encouraging firms to strengthen digital capabilities, while comparatively weak policy and external technical support may limit wider implementation. The environmental context therefore appears partially enabling rather than uniformly supportive, which helps explain its significant but relatively small contribution to AI adoption.

4.4.5. The TOE Model and the Organisational Pathway to AI Adoption

Taken together, the findings indicate that the three TOE contexts are statistically associated with AI adoption, but their contributions differ within the sampled firms. The results therefore support the usefulness of the TOE framework while also demonstrating that its dimensions do not necessarily contribute with equal strength in a particular organisational and institutional context. The comparatively stronger organisational association, alongside moderate overall AI adoption, suggests a gap between internal readiness and the extent to which AI is embedded across project-delivery functions.

The model explained 30.8% of the variance in AI adoption, leaving substantial unexplained variance. This indicates that other determinants not represented in the current TOE specification may also be relevant, including AI trust, perceived risk, data governance, cybersecurity, organisational culture, vendor capability, and workforce attitudes. The findings therefore support TOE as a useful organising framework rather than a complete explanation of AI adoption in Nigerian construction firms.

4.5. Practical Implications for the Nigerian Construction Industry

For construction firms, AI adoption should be approached as an organisational transformation rather than simply a technology-acquisition exercise. Firms should establish clear leadership responsibility for AI, integrate AI objectives into organisational strategies, and develop governance arrangements that guide its implementation across project-delivery functions. Attention should also be given to interoperability with existing digital systems and workflows, supported by targeted workforce development that builds practical AI competencies in design, planning, project control, monitoring, commercial management, procurement, and decision support. This would help firms move from isolated AI applications towards more systematic and integrated use across the project-delivery lifecycle.

For policymakers and professional bodies, there is a need to strengthen the institutional ecosystem supporting responsible AI adoption in construction. This includes developing construction-specific guidance on AI governance, data management, ethical use, professional responsibility, and digital information standards. Professional bodies can further support implementation through competency frameworks, continuous professional development programmes, and industry guidance that equip practitioners to work effectively with AI-enabled technologies. Greater collaboration between government, professional institutions, universities, technology providers, and construction firms could also improve access to technical expertise and facilitate knowledge transfer.

For clients and procurement stakeholders, AI adoption can be encouraged through procurement and project requirements that support structured digital delivery. Clients can incorporate appropriate digital information requirements, BIM provisions, data standards, digital reporting, and performance-monitoring requirements into project briefs and procurement processes. However, these requirements should be proportionate to the capability of project participants and supported by appropriate data, skills, interoperability, and technical infrastructure. A phased approach would therefore be preferable to imposing advanced AI requirements without the organisational and technical conditions necessary for effective implementation.

4.6. Limitations and Future Research

This study has several limitations. First, its cross-sectional design identifies associations rather than causal relationships; longitudinal research is therefore needed to examine how AI adoption develops over time. Second, the purposive and network-based sampling limits generalisation beyond large-scale construction firms represented in the study. Future research should consider larger and probability-based samples, and less digitally mature firms.

Third, the measurement assessment identified convergent and discriminant validity concerns, particularly for the Organisation and Environment constructs. These measures should therefore be refined and revalidated in future studies. Finally, the model explained 30.8% of the variance in AI adoption, indicating that other determinants remain relevant. Future research could examine factors such as AI trust, perceived risk, data governance, cybersecurity, organisational culture, regulatory readiness, and workforce attitudes, including through comparative studies across Nigerian and other Sub-Saharan African construction contexts.

5. Conclusion

The study found that AI adoption among large-scale construction firms in Nigeria remains moderate and unevenly distributed across project-delivery functions, with the greatest reported application occurring in design/BIM and planning/project control. All three TOE dimensions were positively associated with AI adoption, although organisational conditions demonstrated the strongest association. The findings indicate that technological availability and external pressures alone do not fully explain AI adoption; organisational capability, workforce preparedness, innovation orientation, and implementation capacity are also important considerations.

Ethical Considerations and Consent to Participate

In accordance with applicable research guidelines at the Federal University of Technology, Minna, Nigeria, formal ethical approval was considered unnecessary given the study's non-clinical nature and focus on professional opinions. Informed consent was obtained from respondents prior to questionnaire administration through an introductory participant information and consent statement outlining the purpose of the study, the anonymity of responses, and the right to withdraw at any stage without consequence.

Conflict of Interest

The authors declare that they have no conflict of interest.

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Data Availability

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Use of AI-assistance

AI-assisted tools, including SciSpace and Julius AI, were used to support language refinement, editorial structure and to enhance the graphical presentation of the figures.

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