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Original Article

Determinants of Artificial Intelligence Adoption among Small and Medium-Sized Construction Businesses (SMEs) in Nigeria

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Abstract

Artificial Intelligence (AI) is increasingly recognized as a transformative tool for improving efficiency, accuracy, and decision-making in construction project management. Despite its potential, the level of AI adoption among small and medium-sized construction businesses (SMEs) in developing economies remains uneven and poorly understood. This study investigates the key determinants influencing AI adoption among construction SMEs in Nigeria. A quantitative research design was employed, informed by Innovation Diffusion Theory and underpinned by the Technology-Organisation-Environment (TOE) framework and the Technology Acceptance Model (TAM). Data were collected through structured questionnaires administered to 382 randomly selected registered construction SMEs, of which 360 valid responses were analysed. Exploratory factor analysis reduced 18 AI adoption variables into three core dimensions: AI functions, AI utilisation, and perceived AI effectiveness. Multiple regression analysis revealed that Technological Infrastructure Readiness was the strongest positive predictor of AI adoption ($\beta = 0.471$, $p < 0.001$). In contrast, Workforce Training and Skills, Industry Collaboration, Regulatory/Institutional Support, and Top Management Support did not significantly influence AI adoption. High implementation costs, resistance to cultural change, and lack of skilled expertise emerged as significant barriers to AI adoption among Nigeria's construction SMEs. The study contributes empirical evidence from a developing-country construction context. It provides practical insights for policymakers, industry regulators, and SME managers seeking to accelerate digital transformation in Nigeria's construction sector.

Categories: SME Entrepreneurship, Digital business, Organisational Development

Keywords: artificial intelligence, innovation diffusion theory, technology adoption, construction smes, nigeria, barriers, enablers, determinants, ai adoption, toe framework

Introduction

The construction industry plays a crucial role in economic development by driving infrastructure growth, generating employment, and fostering capital formation (Alaloul et al., 2021). In Nigeria, small and medium-sized construction enterprises (SMEs) dominate the sector, contributing significantly to the completion of infrastructure projects (Abada and Okorie, 2016). Despite their importance, these firms continue to face a range of challenges, including frequent cost overruns, project delays, safety issues, and inefficient resource management (Idemudia et al., 2023). These challenges are compounded by a reliance on traditional methods, which limits the potential for improvement and innovation.

In recent years, artificial intelligence (AI) has been touted as a transformative tool that can address many of these inefficiencies in construction project management (Mohite et al., 2023). AI applications, such as machine learning, natural language processing, and computer vision, offer promising solutions to optimize cost estimation, improve scheduling accuracy, enhance safety monitoring, and ensure quality control (Taboada et al., 2023). Globally, construction firms are increasingly adopting AI-driven tools to streamline operations, enhance decision-making, and boost overall project efficiency (Aljebory and QaisIssam, 2019). For instance, studies have shown that AI can improve productivity by automating repetitive tasks, reducing human error, and enabling better resource allocation (Duan et al., 2019). However, the adoption of AI technologies in developing economies, particularly among construction SMEs in Nigeria, remains limited and uneven (Idemudia et al., 2023).

Existing research on AI adoption has largely focused on the technological applications, frameworks, and case studies in developed economies (Duan et al., 2019), (Faheem et al., 2024), and (Fasanghari et al., 2015). These studies provide valuable insights into AI's role in the construction industry, but they do not address the unique challenges faced by SMEs in developing countries. In these contexts, SMEs encounter specific barriers, including limited access to capital, lack of technical expertise, and inadequate infrastructure, which hinder the full integration of digital tools (Idemudia et al., 2023) (Kamal and Flanagan, 2014). For example, the lack of reliable internet connectivity and inadequate digital infrastructure in Nigeria creates significant barriers to AI implementation in construction projects (United Nations, 2024). Furthermore, cultural resistance to change, insufficient workforce training, and a lack of regulatory support further impede the uptake of AI solutions in the sector (Idemudia et al., 2023).

The need for this study arises from the urgent demand for digital transformation in Nigeria's construction sector (Idowu et al., 2023), (Elamah and Eromonsele, 2025), and (Idemudia et al., 2023). Despite the potential of AI to optimize construction processes, increase project efficiency, and enhance safety, the adoption of these technologies remains sluggish. Similarly, existing studies have largely focused on developed economies and large organizations, with limited attention to SMEs in developing countries such as Nigeria. Furthermore, few studies have integrated multiple theoretical perspectives to explain AI adoption comprehensively. This study aims to fill the existing research gap by investigating the key factors that drive or hinder AI adoption among Nigerian construction SMEs. Drawing on established theories such as the Innovation Diffusion Theory (IDT) (Rogers, 2003), the Technology-Organization-Environment (TOE) framework (Baker, 2011), and the Technology Acceptance Model (TAM) (Ma and Liu, 2025), this research explores the technological, organizational, and environmental determinants of AI adoption.

The rationale for this study lies in the critical need for Nigerian construction SMEs to adopt AI in order to stay competitive in an increasingly digital and globalized construction market. The construction industry in Nigeria faces several challenges, including outdated project management practices, inefficiency, and high operational costs. Therefore, AI adoption is not just an opportunity; it is essential for the long-term sustainability of SMEs in the sector. By providing empirical evidence on the enablers and barriers to AI adoption, this study will offer valuable insights for policymakers, industry regulators, and SME managers. The findings aim to contribute to the ongoing digital transformation of the Nigerian construction sector, providing a roadmap for accelerating AI integration and improving project outcomes.

Review of literature

"Artificial intelligence" (AI) refers to computer systems capable of performing tasks that typically require human intelligence, including learning, reasoning, prediction, and pattern recognition (Bin Rashid and Kausik, 2024). Within the construction industry, AI applications support project planning, cost estimation, scheduling, risk management, quality control, safety monitoring, and resource optimization (Taboada et al., 2023). These capabilities have the potential to improve project performance through enhanced decision-making, automation, and operational efficiency.

Despite these benefits, AI adoption within the construction sector remains relatively slow, particularly among SMEs in developing countries (Idowu et al., 2023). Construction SMEs often face constraints related to financial resources, technical expertise, and digital infrastructure, limiting their ability to implement advanced technologies (Idemudia et al., 2023) (Kamal and Flanagan, 2014). In Nigeria, challenges such as inadequate digital infrastructure, skills shortages, and weak institutional support further hinder the adoption of AI-enabled solutions (United Nations, 2024) (Idemudia et al., 2023).

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This study conceptualizes AI adoption across major project management functions, including project initiation, planning, budgeting, design, resource management, quality management, risk management, construction monitoring, stakeholder communication, health and safety management, and project closure. Table 1 presents key AI integration strategies and applications across these project management activities (PMI, 2017).

Project Management Task	AI Tech	AI Integration Strategies	AI Use Case	Reference (Author)
Project Initiation	Predictive Analytics	AI-driven tools for feasibility, cost, and risk forecasting	Predictive analytics for assessing project feasibility, estimating costs, and identifying potential risks	(PMI, 2025a)
Project Planning	Machine Learning (ML)	ML-driven scheduling and automated task planning for efficiency	AI-based systems for automating task planning and optimizing project timelines	(Aljebory and QaisIssam, 2019)
Budgeting and Cost Management	Predictive Analytics and Financial Forecasting Tools	AI-enhanced cost estimation, financial forecasting using historical data and trends	AI for dynamic budget updates and predictive cost forecasting based on historical data	(Mohite et al., 2023)
Design and Documentation	AI-integrated Building Information Modeling (BIM), Energy Optimization Systems	AI-enhanced BIM for design integration, energy simulations, and sustainable architecture planning	AI-enabled BIM tools for energy optimization, material selection, and project lifecycle management	(Alizadehsalehi and Yitmen, 2023)
Resource Management	Supply Chain Optimization using AI	AI-driven algorithms to predict material demand, automate procurement processes, and optimize supply chains	AI-based supply chain management to predict material shortages and reduce procurement delays	(Mohite et al., 2023)
Quality Management	AI-based Inspection and Compliance Verification Tools	Automated compliance verification through AI-driven inspection systems, visual recognition software	AI systems used for inspecting construction quality, detecting deviations from standards, and ensuring compliance	(Rane et al., 2024) (Taboada et al., 2023)
Risk Management	Predictive Analytics for Risk Detection	AI-enabled tools to detect risks early through data analysis, enabling proactive risk mitigation	Real-time risk monitoring and predictive analytics for identifying project risks and suggesting contingency plans	(Aladağ, 2023) (PMI, 2025a)

Construction Execution & Monitoring	AI-driven Performance Monitoring and Optimization Systems	Real-time monitoring of project performance and energy optimization using AI tools	AI systems that monitor construction sites in real-time, optimizing energy use and tracking progress	(Alizadehsalehi and Yitmen, 2023) (Mohite et al., 2023)
Communication & Stakeholder Management	AI-powered Collaboration Tools, chatbots, and Real-time Dashboards	AI-based platforms for collaboration, communication, and reporting in real-time	Use of chatbots for instant responses, AI dashboards for reporting, and predictive tools for stakeholder management	(Pérez Vera and Bermudez Peña, 2018)
Health & Safety Management	Computer Vision and AI-based Hazard Detection Tools	Integration of computer vision technologies to identify potential safety hazards and violations in real-time	AI-driven image recognition systems used for monitoring construction sites and detecting safety hazards	(Mandičák and Spišáková, 2024) (Nnaji et al., 2020)
Project Closure	AI-driven Evaluation and Reporting Tools	Automated generation of project evaluation reports, post-project analysis through AI-powered systems	AI for post-project analysis, including performance assessments, cost reconciliation, and final reporting	(Alizadehsalehi and Yitmen, 2023) (PMI, 2025b)

TABLE 1: AI Integration Strategies in Construction Project Management Tasks

Source: Author. AI, Artificial intelligence

Theoretical foundation

The study draws upon three complementary theoretical perspectives: IDT (Rogers, 2003), TOE framework (Baker, 2011), and TAM (Köck, 2017). Together, these frameworks provide a comprehensive explanation of technological, organizational, environmental, and behavioral factors influencing AI adoption among construction SMEs.

IDT explains how innovations spread within a social system and identifies five key attributes that influence adoption decisions: relative advantage, compatibility, complexity, trialability, and observability (Rogers, 2003). In the context of AI adoption, technologies perceived as beneficial, compatible with existing practices, and easy to experiment with are more likely to be adopted.

The TOE framework emphasizes that technology adoption is influenced by technological readiness, organizational capabilities, and environmental conditions (Baker, 2011). For construction SMEs, factors such as infrastructure availability, leadership support, workforce competence, and regulatory conditions may significantly affect AI implementation decisions.

The TAM focuses on individual perceptions of technology, particularly perceived usefulness and perceived ease of use (Köck, 2017). Construction professionals are more likely to embrace AI solutions when they believe such technologies can improve project outcomes and can be integrated into existing workflows with minimal difficulty.

Conceptual framework and hypotheses development

Drawing from these theoretical perspectives, this study proposes that AI adoption among Nigerian construction SMEs is influenced by both enabling and inhibiting factors. Enablers include technological readiness, organizational support, workforce capability, and perceived effectiveness of AI applications. Prior studies have shown that AI technologies can improve project planning, cost estimation, scheduling accuracy, safety monitoring, and risk management, thereby increasing their perceived value to construction organizations (Mohite et al., 2023) (Nwankwo et al., 2024). Conversely, barriers such as high implementation costs, limited technical expertise, resistance to organizational change, and inadequate digital infrastructure may constrain adoption efforts (Dindorf and Wos, 2024), (Oke et al., 2024), and (Oladinrin et al., 2025). These constraints are particularly pronounced among SMEs operating in developing economies, where resources and institutional support remain limited. Accordingly, the study hypothesizes the following:

H_1: IDT enablers have a significant positive effect on AI adoption for project management practices in Nigeria's construction sector.

H_2: IDT barriers have a significant negative effect on AI adoption for project management practices in Nigeria's construction sector.

To ensure theoretical alignment, study variables were mapped to the three underpinning theories. Technological infrastructure readiness was derived from the technological dimension of TOE; organizational factors such as management support were linked to the organizational dimension of TOE; and perceived effectiveness was grounded in TAM, while innovation-related constructs were informed by IDT. Figure *1* illustrates the conceptual framework underpinning the study.

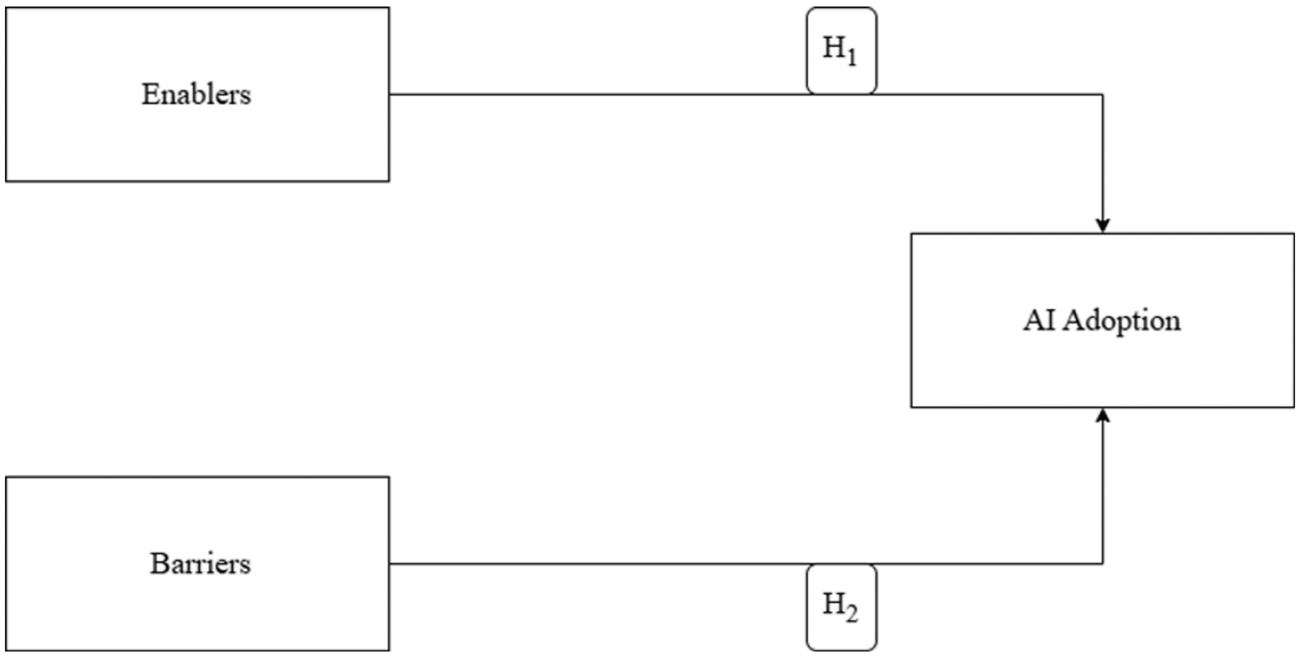

FIGURE 1: Conceptual Framework for Determinants of AI Adoption

Source: Author. AI, Artificial intelligence

Research Method

A quantitative cross-sectional survey design was adopted to investigate the determinants of AI adoption among SMEs in Nigeria. The study was grounded in the positivist research philosophy, which assumes that relationships among variables can be objectively measured and statistically analyzed using empirical data (McNabb, 2020). While qualitative methods could provide in-depth insights into individual and organizational adoption processes, a quantitative approach was deemed more effective for generalizing results across a broader range of firms and ensuring the external validity of the findings.

The target population comprised 8,523 registered construction SMEs operating in Nigeria, obtained from the Corporate Affairs Commission database and industry directories (Rentech Digital, 2025). Construction SMEs were selected because they constitute a significant proportion of construction firms in Nigeria and play a critical role in project delivery and infrastructure development. The unit of analysis was the construction SME firm, while respondents consisted of key professionals and management personnel directly involved in project management and technology-related decision-making. These included project managers, builders, quantity surveyors, architects, engineers, company directors, and other senior personnel within construction SMEs. The sample size was determined using the Yamane (Yamane, 1967) finite population formula at a 95% confidence level and 5% margin of error, resulting in a minimum sample size of 382 SMEs. This sample size was considered adequate for multivariate statistical analysis and factor analysis, consistent with recommendations by Hair and Alamer (Hair and Alamer, 2022).

A multistage sampling procedure was adopted. In the first stage, registered construction SMEs were randomly selected from available industry directories and professional databases to ensure broad representation across the population. In the second stage, purposive sampling was employed to identify respondents with sufficient knowledge of project management practices and AI applications within the selected firms. Given the emerging nature of AI adoption among Nigerian construction SMEs, snowball sampling was subsequently utilized through professional networks and industry referrals to reach additional qualified respondents. The combination of random, purposive, and snowball sampling enhanced access to information-rich respondents and improved response coverage.

Data were collected using a structured questionnaire developed for this study. The survey was structured into four sections to capture comprehensive data on the determinants of AI adoption among construction SMEs in Nigeria. Section A captured firm characteristics, including size, type of work, and years of operation. Section B examined AI adoption practices across project management functions and assessed the perceived effectiveness of AI tools. Section C assessed the perceived benefits motivating AI adoption among construction SMEs, while Section D examined barriers to AI adoption, including high implementation costs, lack of skilled labor, and resistance to technological change.

Each construct representing the determinants of AI adoption, grounded in IDT, was operationalized as a latent variable and measured using a five-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). Specifically, eighteen items assessed AI adoption practices, sixteen items evaluated adoption enablers, and fifteen items examined adoption barriers. Although some items within each construct were conceptually related, multiple indicators were intentionally retained to ensure adequate measurement of latent constructs and improve construct reliability. Subsequent exploratory factor analysis confirmed that the items loaded appropriately on their respective factors, thereby supporting construct validity.

The questionnaire was adapted to the Nigerian construction context through multiple rounds of expert validation. The instrument was pre-tested by five professors of construction management, ten experts in AI applications within construction, and twenty experienced construction SME operators. The pre-test assisted in identifying potential errors, refining item wording, and improving the clarity and reliability of the instrument (Creswell, 2018).

The final questionnaire was administered both physically and electronically through emails, WhatsApp platforms, professional associations, and direct organizational contacts. A total of 382 questionnaires were distributed, of which 360 valid responses were retrieved and utilized for analysis, representing a response rate of approximately 94%.

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Ethical principles were observed throughout the study. Participation was entirely voluntary, and respondents were informed of the academic purpose of the research before participation. Confidentiality and anonymity were assured, and respondents were informed that all information provided would be used strictly for academic and research purposes. No personally identifiable information was collected or disclosed.

Because data were collected using a self-administered questionnaire and a cross-sectional survey design, procedural and statistical remedies were employed to minimize common method bias (CMB). Procedurally, respondents were assured of anonymity and confidentiality to reduce evaluation apprehension and social desirability bias. Questionnaire items were carefully worded to minimize ambiguity, while predictor and outcome variables were organized into separate sections of the questionnaire. Statistically, Harman's single-factor test was conducted using exploratory factor analysis. The first unrotated factor accounted for 39.73% of the total variance, which is below the recommended threshold of 50%, indicating that CMB was not a significant concern in this study (Field, 2024).

Data analysis methods

The data were analyzed using both descriptive and inferential statistical techniques. Descriptive statistics, including frequencies, percentages, means, and standard deviations, were used to summarize the demographic characteristics of respondents and organizational attributes of participating firms. This provided a contextual understanding of the sample and the profile of construction SMEs involved in the study.

For the inferential analysis, Exploratory Factor Analysis (EFA) was performed using Principal Component Analysis (PCA) with Varimax rotation to identify the underlying dimensions of AI adoption, adoption enablers, and adoption barriers. The suitability of the data for factor analysis was assessed using the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and Bartlett's Test of Sphericity. The KMO value of 0.877 exceeded the recommended threshold of 0.60, confirming the adequacy of the sample for factor analysis (Kaiser, 1974). Factors with eigenvalues greater than 1.0 were retained, while the scree plot was used to confirm the factor structure. Varimax rotation was applied to improve factor interpretability by maximizing factor loadings and reducing cross-loadings. Internal consistency, reliability, and validity of the extracted constructs were assessed using Cronbach's alpha coefficients, average variance extracted (AVE), and composite reliability (CR).

Although Confirmatory Factor Analysis (CFA) could provide additional validation of the measurement constructs, the present study adopted an exploratory approach aimed at identifying the underlying dimensions influencing AI adoption among construction SMEs. Therefore, EFA was considered appropriate at this stage. Future studies may extend the analysis using CFA or Structural Equation Modeling (SEM) to further validate the proposed measurement model.

Following factor extraction, multiple regression analysis was employed to examine the influence of adoption enablers and barriers on AI adoption. AI adoption served as the dependent variable, while the extracted enabler and barrier dimensions were entered as independent variables. The coefficient of determination (R^2) was used to assess the explanatory power of the regression model, while standardized regression coefficients were used to evaluate the relative contribution of each predictor. Statistical significance was assessed at $p < 0.05$ and $p < 0.01$ levels, and t-tests were used to evaluate the significance of individual regression coefficients.

All statistical analyses were conducted using SPSS version 27 and Microsoft Excel. Before regression analysis, key assumptions, including normality, linearity, homoscedasticity, independence of errors, multicollinearity, and sample adequacy, were assessed and found to be satisfactory. This assured the robustness and reliability of the analytical results. In addition, Harman's single-factor test was conducted to assess CMB, with the first unrotated factor accounting for 39.73% of the total variance, indicating that CMB was not a significant concern.

Results And Discussion

Respondent profile and organizational attributes

Table *2* summarizes the demographic characteristics of respondents and organizational attributes of participating construction firms. The majority (76%) of respondents were male, while 24% were female, reflecting the gender composition typical of the Nigerian construction industry. Approximately 68% of the respondents occupied management positions such as project managers, quantity surveyors, or builders, ensuring informed responses grounded in professional experience. Over 70% of respondents reported more than ten years of industry experience, while 58% possessed at least a bachelor's degree or its equivalent. This distribution suggests that the dataset represents an informed and technically competent population. Regarding firm characteristics, 49% of firms employed 1-49 staff, 33% had 51-199 staff, and 18% employed over 200 permanent staff. This diversity demonstrates that both medium and large firms are represented in the sample. Nearly half (47%) specialized in building construction, while the remainder operated in civil and infrastructure works. Such diversity in firm size, experience, and operational scope enhances the generalizability of the findings across Nigeria's construction industry.

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Category	Frequency (n)	Percentage (%)
Gender		
Male	274	76
Female	86	24
Position/Role		
Project Manager	101	28
Quantity Surveyor	79	22
Builders	65	18
Architect	43	12
Other (Planner, Land & Estate Surveyors, etc.)	72	20
Years of Industry Experience		
Less than 5 years	36	10
5–10 years	68	19
More than 10 years	256	71
Educational Qualification		
Diploma/OND	54	15
Bachelor’s Degree	209	58
Postgraduate Degree (MSc/PhD)	97	27
Firm Size		
Small (1–49 employees)	176	49
Medium (50–199 employees)	119	33
Large (200+ employees)	65	18
Type of Construction Work		
Building Construction	169	47

Civil/Infrastructure Works	191	53

TABLE 2: Respondent Profile and Organizational Attributes (n = 360)

Source: Author

EFA of AI adoption practices

An EFA using PCA with Varimax rotation was conducted to determine the dimensionality of the AI adoption construct. Sampling adequacy was confirmed by a KMO value of 0.877, classified as meritorious (Kaiser, 1974). Bartlett's Test of Sphericity was also significant ($\chi^2 = 4308.684$, df = 153, $p < 0.001$), confirming the data's suitability for factor analysis. The questionnaire contained 18 items relating to AI adoption in project management. As shown in Table *3*, three factors with eigenvalues >1 were extracted, explaining 66.2% of the total variance well above the recommended threshold of 50% (Shrestha, 2021) (Alara, 2021). The rotated component matrix confirmed strong loadings (>0.60) on their respective factors with minimal cross-loadings. Items 1-6 loaded on Factor 1: AI Functions, representing the functions AI tools currently perform in construction projects. This factor explained 22.12% of the variance (eigenvalue = 3.982). Items 7-12 loaded on Factor 2: AI Utilization, capturing the extent to which firms actively deploy AI tools in practice, explaining 21.92% of the variance (eigenvalue = 3.946). Finally, items 13-18 loaded on Factor 3: AI Effectiveness, reflecting perceptions of how effectively AI tools meet project management needs. This explained 22.14% of the variance (eigenvalue = 3.986). All factor loadings exceeded 0.60, and except for one retained item, communalities exceeded the recommended threshold of 0.50. Most communalities exceeded the recommended threshold of 0.50. The retained Computer Vision item exhibited a communality of 0.469 but was retained because it demonstrated a strong factor loading and substantial theoretical relevance.

Although the retained Computer Vision item exhibited a communality of 0.469, it was retained because of its strong factor loading and theoretical relevance (Field, 2024) (Hair and Alamer, 2022), thereby supporting the construct validity of the measurement model. Importantly, the factor analysis identified three dimensions of AI adoption that are theoretically consistent with the Innovation Diffusion Theory (IDT), the Technology-Organisation-Environment (TOE) framework, and the Technology Acceptance Model (TAM). The first dimension, AI Functions, represents the functional capabilities of AI tools in construction project management and aligns with Rogers' (Rogers, 2003) concept of relative advantage within IDT. The second dimension, AI Utilisation, captures the extent to which firms actively deploy AI tools in practice, aligning with the IDT attribute of observability, whereby visible use of AI technologies enhances awareness and encourages broader organisational adoption. The third dimension, AI Effectiveness, aligns with the perceived usefulness construct of TAM, reflecting users' perceptions of the extent to which AI improves project management performance and project outcomes. These findings provide empirical support for the construct validity of the AI adoption measurement model and demonstrate its theoretical consistency with the underpinning theoretical frameworks.

S/N	Variables	Rotated Factor loadings			Communality
		Factor 1	Factor 2	Factor 3	
	AI Functions				
1	AI cost estimation & budgeting	**0.816**	0.242	0.108	0.651
2	AI-assisted design & planning	**0.810**	0.225	0.034	0.669
3	AI-driven project scheduling	**0.792**	0.073	0.139	0.614
4	AI-powered communication & reporting	**0.763**	0.275	0.106	0.736
5	AI-based safety monitoring	**0.740**	0.173	0.189	0.708
6	AI-supported quality assurance	**0.716**	0.258	0.163	0.607
	AI Utilization				
7	Use of computer vision	0.181	**0.869**	0.215	0.469
8	Use of natural language processing (NLP)	0.217	**0.808**	0.23	0.753
9	Adoption of AI cost estimation tools	0.237	**0.750**	0.279	0.697
10	Application of machine learning	0.229	**0.720**	0.199	0.611
11	AI-enabled Building Information Modeling (BIM)	0.269	**0.709**	0.248	0.835
12	Deployment of AI scheduling tools	0.193	**0.618**	0.222	0.637
	AI Effectiveness				

13	Perceived effectiveness of NLP applications	0.125	0.122	**0.852**	0.654
14	Perceived effectiveness of computer vision solutions	0.116	0.231	**0.797**	0.756
15	Perceived effectiveness of machine learning applications	0.1	0.234	**0.768**	0.701
16	Perceived effectiveness of AI cost estimation software	0.113	0.18	**0.743**	0.592
17	Perceived effectiveness of AI scheduling tools	0.143	0.255	**0.736**	0.597
18	Perceived effectiveness of AI-enabled BIM	0.134	0.253	**0.714**	0.627
	Eigen value	3.982	3.946	3.986	
	% of Total Variance	22.121	21.922	22.144	
	Total variance			66.187 %	

TABLE 3: Exploratory Factor Analysis for AI Adoption Practices

Loadings ≥0.60 are highlighted in bold. AI, Artificial intelligence
Source: Author

EFA for enablers of AI adoption

PCA with Varimax rotation confirmed the factor structure of the enablers. The KMO measure of sampling adequacy was 0.870, exceeding the recommended threshold of 0.70 (Kaiser, 1974). Bartlett's test of sphericity was significant (χ^2 = 2828.889, df = 120, p < 0.001), confirming suitability for factor analysis. The results in Table *4* show that the rotated component matrix revealed a five-factor solution, explaining 72.3% of the total variance, corresponding to the pre-identified dimensions. The first factor (Industry Support) explained 17.996% of the variance with an eigenvalue of 2.879; the second factor (Technological Support) explained 14.89% of the variance with an eigenvalue of 2.384; the third factor (Top Management Support) explained 14.725% of the variance with an eigenvalue of 2.356; the fourth factor (Workforce Training and Skills) explained 13.603% of the variance with an eigenvalue of 2.176; and the fifth factor (Regulatory &

Institutional) explained 11.114% of the variance with eigenvalue 1.778. All items loaded strongly (> 0.70) on their respective constructs with minimal cross-loadings, supporting dimensional distinctiveness and convergent validity. Additionally, the rotation yielded acceptable communalities > 0.5, indicating high item relevance.

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Code	Variables	F1:Industry Support	F2:Tech. Support	F3:Top Mgmt. Support	F4:Training & Skills	F5: Regulatory Support	Communality
	Industry Support						
IS1	Industry-driven policies and initiatives	**0.820**	0.201	0.185	0.188	0.052	0.706
IS2	Industry collaboration and partnerships	**0.782**	0.102	0.138	0.096	0.223	0.700
IS3	Availability of industry resources and funding	**0.781**	0.125	0.163	0.086	0.291	0.744
IS4	Industry support for AI adoption	**0.763**	0.191	0.226	0.188	0.026	0.784
	Technological Support						
TS1	Availability of advanced technological infrastructure	0.202	**0.854**	0.215	0.164	-0.082	0.850
TS2	Access to AI tools and platforms	0.136	**0.823**	0.187	0.137	0.227	0.800
TS3	Integration of AI with existing systems	0.219	**0.791**	0.175	0.103	0.275	0.791
	Top Management Support						
TMS1	Commitment of top	0.104	0.215	**0.750**	0.092	0.265	0.591

	management to AI initiatives						
TMS2	Allocation of resources by leadership	0.175	0.059	**0.726**	0.147	0.000	0.698
TMS3	Strategic vision for AI adoption	0.178	0.195	**0.693**	0.176	-0.097	0.614
TMS4	Encouragement and support from executives	0.208	0.165	**0.670**	0.023	0.308	0.582
	Workforce Training and Skills						
TC1	Availability of AI-related training programs	0.145	0.214	0.194	**0.826**	-0.042	0.789
TC2	Skill development opportunities for employees	0.176	0.161	0.113	**0.789**	0.274	0.768
TC3	Continuous professional development in AI	0.175	0.018	0.124	**0.759**	0.388	0.773
	Regulatory & Institutional						
RS1	Institutional policies enabling AI adoption	0.28	0.076	0.091	0.222	**0.771**	0.647
RS2	Supportive regulatory frameworks for AI	0.139	0.236	0.146	0.200	**0.714**	0.736
	Eigen value	2.879	2.384	2.356	2.176	1.778	

	% of Total Variance	17.996	14.89	14.725	13.603	11.114	
	Total variance					72.34 %	

TABLE 4: Exploratory Factor Analysis for Enablers of AI Adoption (N = 360)

Loadings ≥0.60 are highlighted in bold. AI, Artificial intelligence
Source: Author

EFA for barriers to AI adoption

Principal Component Analysis (PCA) with Varimax rotation was conducted to examine the factorial structure of the barriers to AI adoption. The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy was 0.900, exceeding the recommended threshold of 0.70 (Kaiser, 1974). Bartlett's Test of Sphericity was statistically significant ($\chi^2 = 4943.275$, df = 105, $p < 0.001$), confirming the suitability of the data for factor analysis. As presented in Table *5*, the rotated component matrix produced a five-factor solution explaining 86.583% of the total variance, corresponding to the theoretically derived barrier dimensions. The first factor, High Implementation Costs, explained 19.174% of the variance (eigenvalue = 2.876); the second, Data Availability & Quality, explained 18.290% (eigenvalue = 2.744); the third, Technical Complexity & Integration, explained 16.796% (eigenvalue = 2.519); the fourth, Lack of Skilled Expertise, explained 16.600% (eigenvalue = 2.490); and the fifth, Resistance to Cultural Change, explained 15.719% (eigenvalue = 2.358). The fourth, Resistance to Cultural Change indicator ("Inadequate digital connectivity, power supply, and systems integration") was removed during Exploratory Factor Analysis because it did not satisfy the required factor loading and communality criteria and was therefore excluded from the final measurement model. All retained items loaded strongly (>0.70) on their respective constructs with minimal cross-loadings, supporting dimensional distinctiveness and convergent validity. Furthermore, all retained items exhibited communalities exceeding the recommended threshold of 0.50, indicating adequate shared variance among the items. The five-factor solution was both statistically robust and conceptually meaningful. The high KMO value (0.900) and significant Bartlett's test confirmed sampling adequacy, while the strong factor loadings and satisfactory communalities supported the construct validity of the measurement model. The extracted factors are consistent with the barrier dimensions identified in previous AI adoption studies and reinforce the multidimensional conceptualisation of AI adoption barriers within the Innovation Diffusion Theory (IDT) perspective (Rogers, 2003), (Elamah and Eromonsele, 2025), (Idemudia et al., 2023), (Idowu et al., 2023), and (Pittri et al., 2025).

Code	Variables	F1: High Cost	F2: Data Qtly	F3:Top Technical	F4: Lack skills	F5: Culture	Communality
	High Implementation Costs						
HC1	The financial investment required for adoption is perceived as excessive	**0.901**	0.148	0.101	0.119	0.274	0.913
HC2	Limited budgets and resource constraints restrict the ability to implement new systems	**0.889**	0.189	0.128	0.15	0.22	0.933
HC3	Ongoing operational and maintenance costs are seen as unsustainable	**0.871**	0.212	0.085	0.149	0.297	0.922
	Data Availability & Quality						
DA1	Reliable and high-quality data are often lacking for effective decision-making	0.224	**0.873**	0.214	0.194	0.174	0.916
DA2	Data access is fragmented, inconsistent, or incomplete	0.157	**0.867**	0.215	0.199	0.19	0.926

	across systems						
DA3	Concerns about data accuracy reduce confidence in its usefulness	0.197	**0.863**	0.209	0.213	0.21	0.898
	Technical Complexity & Integration						
TC1	Integrating new technologies with existing infrastructure is technically challenging	0.107	0.14	**0.875**	0.16	0.119	0.837
TC2	Complex system requirements hinder smooth implementation	0.102	0.18	**0.851**	0.263	0.119	0.851
TC3	Lack of interoperability between platforms creates additional technical barriers	0.089	0.274	**0.794**	0.206	0.186	0.791
	Lack of Skilled Expertise						
SE1	There is a shortage of staff with the necessary technical knowledge	0.169	0.13	0.221	**0.844**	0.19	0.816

SE2	Limited training opportunities restrict capacity building	0.101	0.215	0.234	**0.825**	0.122	0.808
SE3	Dependence on external expertise increases reliance and vulnerability	0.152	0.239	0.198	**0.795**	0.255	0.842
	Resistance to Cultural Change						
RC1	Organizational culture resists new approaches or innovations	0.314	0.176	0.157	0.178	**0.833**	0.844
RC2	Employees are reluctant to adapt established practices	0.269	0.252	0.208	0.21	**0.788**	0.879
RC3	Fear of uncertainty and loss of control fuels resistance to change	0.372	0.204	0.137	0.265	**0.736**	0.812
	Eigen value	2.876	2.744	2.519	2.490	2.358	
	% of Total Variance	19.174	18.29	16.796	16.60	15.719	
	Total variance					86.58%	

TABLE 5: Exploratory Factor Analysis for Barriers to AI Adoption (N = 360)

Loadings ≥0.60 are highlighted in bold. AI, Artificial intelligence
Source: Author

Reliability, AVE, and CR

Table *6* presents the reliability and validity statistics for all 13 constructs, including Cronbach's alpha (α), Average Variance Extracted (AVE), and Composite Reliability (CR). Cronbach's alpha values were acceptable for all constructs. Although Regulatory & Institutional Support recorded a Cronbach's alpha of 0.680, values approaching 0.70 are considered acceptable in exploratory research and were further supported by satisfactory Composite Reliability (CR = 0.711) and Average Variance Extracted (AVE = 0.552) (Hair and Alamer, 2022). These results indicate acceptable internal consistency and confirm the reliability of the measurement instrument. Overall, the AI adoption, enabler, and barrier constructs demonstrated satisfactory reliability, supporting the robustness of the measurement scales. Furthermore, all AVE values exceeded the recommended threshold of 0.50, indicating adequate convergent validity, while all CR values exceeded the recommended threshold of 0.60, providing additional evidence of construct reliability (Hair and Alamer, 2022).

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Constructs	Reliability (Cronbach's alpha)	AVE	CR
AI Adoption			
AI Functions	0.895	0.599	0.899
AI Utilizations	0.897	0.562	0.884
AI Effectiveness	0.893	0.592	0.897
Enablers of AI Adoption			
Industry Support	0.866	0.619	0.867
Technological Support	0.869	0.677	0.863
Top Management Support	0.757	0.505	0.803
Workforce Training and Skills	0.819	0.627	0.834
Regulatory & Institutional	0.680	0.552	0.711
Barriers to AI Adoption			
High Implementation Costs,	0.957	0.787	0.917
Data Availability & Quality	0.953	0.753	0.901
Technical Complexity & Integration	0.889	0.707	0.878
Lack of Skilled Expertise	0.887	0.675	0.862
Resistance to Cultural Change	0.904	0.619	0.829

TABLE 6: Reliability, AVE, and CR

Thresholds: $\alpha \geq 0.70$; CR ≥ 0.70; AVE ≥ 0.50. AVE, Average Variance Extracted; CR, Composite Reliability
Source: Author

Multiple regression of enablers on AI adoption practices among construction SMEs

Multiple regression analysis was performed to assess the influence of five enabler dimensions on AI adoption, with AI adoption as the dependent variable. Table 7 shows that the regression model was statistically significant, $F(5, 354) = 20.203$, $p < .001$, and accounted for 22.2% of the variance in AI adoption ($R^2 = 0.222$), indicating a moderate effect size (Cohen, 1988). Among the predictors, Technological Infrastructure Readiness was the strongest positive predictor of AI adoption ($\beta = 0.471$, $p < 0.001$), indicating that improved technological infrastructure significantly promotes AI adoption. In contrast, Workforce Training and Skills, Industry Collaboration, Regulatory/Institutional Support, and Top Management

Support did not significantly influence AI adoption, suggesting that these factors may require stronger organizational alignment and digital readiness to produce measurable effects. Overall, although the regression model was statistically significant, only Technological Infrastructure Readiness significantly predicted AI adoption. Therefore, Hypothesis H1 was partially supported.

Variables	B	Std. Error	Β	t	Sig.
(Constant)	2.175	0.292	—	7.453	0.000
Technological Infrastructure Readiness	0.345	0.042	0.471	8.195	0.000
Workforce Training & Skills	0.024	0.053	0.026	0.452	0.651
Industry Collaboration	0.010	0.058	0.010	0.176	0.860
Regulatory/Institutional Support	-0.018	0.063	-0.016	-0.278	0.781
Top Management Support	-0.026	0.078	-0.019	-0.328	0.743

TABLE 7: Regression Results - Effects of Enablers on AI Adoption (N = 360)

Model Summary: R = 0.471, R^2 = 0.222, Adj. R^2 = 0.211, F(5, 354) = 20.203, p < .001. AI, Artificial intelligence
Source: Author

Multiple regression of barriers to AI adoption practices among construction SMEs

The multiple regression analysis of barriers to AI adoption revealed a strong explanatory power, with barriers collectively accounting for 72% of the variance in AI adoption (R^2 = 0.720). The model was statistically significant, F(5, 354) = 182.447, p < .001. The results in Table *8* indicated that High Implementation Costs (β = -0.383, p < 0.001), Resistance to Cultural Change (β = -0.341, p < 0.001), and Lack of Skilled Expertise (β = -0.319, p < 0.001) were significant negative predictors of AI adoption. These findings suggest that financial limitations, cultural resistance, and skills gaps present the most significant barriers to AI adoption within Nigeria's construction SMEs. In contrast, technical complexity and data availability and quality were not statistically significant, suggesting that firms currently face fewer challenges in these areas compared to financial and workforce-related issues. Accordingly, although the regression model was statistically significant, only three of the five barrier dimensions significantly influenced AI adoption. Therefore, Hypothesis H2 was partially supported. Table *9* summarises the outcomes of hypothesis testing.

Variables	B	Std. Error	β	t	Sig.
(Constant)	5.199	0.076	—	68.206	0.000
High Implementation Costs	-0.251	0.025	-0.383	-10.203	0.000
Resistance to Cultural Change	-0.230	0.028	-0.341	-8.086	0.000
Lack of Skilled Expertise	-0.268	0.031	-0.319	-8.594	0.000
Technical Complexity & Integration	0.006	0.027	0.007	0.208	0.835
Data Availability & Quality	0.018	0.027	0.025	0.679	0.498

TABLE 8: Regression Results - Effects of Barriers on AI Adoption (N = 360)

Model Summary: R = 0.849, R^2 = 0.720, Adj. R^2 = 0.716, F(5,354) = 182.447, p < .001. AI, Artificial intelligence
Source: Author

Hypothesis	Statement	Decision
H1	IDT enablers have a significant positive effect on AI adoption for project management practices in Nigeria's construction sector.	Partially Supported
H2	IDT barriers have a significant negative effect on AI adoption for project management practices in Nigeria's construction sector.	Partially Supported

TABLE 9: Summary of Hypothesis Testing

Discussion

This study aimed to explore the key enablers and barriers influencing AI adoption among SMEs in Nigeria. The findings provide important insights into how technological, organizational, and environmental factors shape AI adoption decisions within the Nigerian construction industry. More broadly, the study contributes to the growing discourse on digital transformation in developing economies, where the adoption of emerging technologies such as AI remains relatively slow and uneven.

The findings indicate that technological infrastructure readiness was the strongest enabler of AI adoption. This finding is consistent with the TOE framework, which emphasizes the importance of technological readiness as a prerequisite for successful technology implementation (Baker, 2011). Construction SMEs require reliable internet connectivity, digital platforms, data management systems, and supporting hardware infrastructure before advanced AI applications can be effectively deployed. In the Nigerian context, persistent challenges relating to digital infrastructure, electricity supply, internet reliability, and technology investment continue to affect the capacity of firms to adopt advanced digital solutions. This finding supports previous studies that identified inadequate technological infrastructure as a major constraint to digital transformation within the construction sector (Idemudia et al., 2023) (United Nations, 2024). The result suggests that improvements in technological infrastructure may yield greater AI adoption outcomes than isolated investments in AI software alone.

Interestingly, top management support and regulatory support were found to be statistically insignificant predictors of AI adoption. The insignificance of top management support may reflect the operational realities of many Nigerian construction SMEs, where managerial commitment alone may not translate into technology adoption without adequate financial resources, technical expertise, and digital infrastructure. Although managers may recognize the strategic value of AI, implementation decisions are often constrained by cost considerations and operational limitations. Similarly, the insignificant effect of regulatory and institutional support may indicate that AI-specific regulations, incentives, and policy frameworks within Nigeria's construction industry are still evolving and have not yet reached a level capable of significantly influencing organizational adoption behavior. These findings suggest that internal technological preparedness currently exerts a stronger influence on AI adoption decisions than external institutional pressures.

The study further identified high implementation costs, cultural resistance, and lack of skilled expertise as major barriers to AI adoption. These findings reflect challenges commonly reported in developing economies where resource limitations constrain digital innovation and technology investments. High implementation costs remain particularly problematic for SMEs, which often operate with limited financial capacity and may perceive AI investments as risky due to uncertain returns and long payback periods. Consequently, even when firms acknowledge the potential benefits of AI, financial constraints may delay or prevent adoption.

The finding regarding cultural resistance highlights the persistence of traditional work practices within the construction industry. Construction activities in Nigeria remain heavily dependent on established methods, informal decision-making processes, and conventional project management approaches. As a result, employees and managers may be reluctant to adopt unfamiliar technologies that require changes to existing workflows and organizational routines. This finding supports earlier observations by Idowu et al. (Idowu et al., 2023), who noted that resistance to change remains a significant obstacle to digital transformation within the construction sector.

Similarly, the lack of skilled expertise emerged as a significant barrier, underscoring the importance of human capital in successful AI implementation. AI technologies require specialized competencies in data management, digital systems, analytics, and technology integration. However, many construction SMEs face shortages of personnel with the necessary technical capabilities to deploy and manage AI-based systems effectively. This finding aligns with (Pradhan and Saxena, 2023), who reported that inadequate technical skills remain one of the most critical obstacles to the adoption of emerging technologies. The result suggests that investments in workforce development and AI-related training programs may be as important as investments in technology infrastructure.

Another important finding relates to AI effectiveness, which emerged as a significant determinant of adoption. This result supports the TAM, which posits that perceived usefulness is a key driver of technology adoption (Köck, 2017). Construction SMEs are more likely to adopt AI solutions when they perceive tangible benefits in areas such as project planning, cost estimation, safety monitoring, risk management, and resource allocation. The significance of AI effectiveness suggests that adoption decisions are strongly influenced by practical performance outcomes rather than technological novelty. This finding is consistent with studies conducted in both developed and emerging economies, where organizations increasingly adopt AI technologies to improve productivity, enhance decision-making quality, and reduce operational risks (Aljebory and QaisIssam, 2019) (Taboada et al., 2023).

Overall, the findings demonstrate that AI adoption among Nigerian construction SMEs is influenced by a combination of technological readiness, perceived effectiveness, organizational capabilities, and contextual constraints. While AI offers significant opportunities for improving project management performance, successful adoption requires not only technological investments but also workforce development, infrastructure enhancement, and targeted interventions aimed at reducing financial and cultural barriers.

Study limitations and future research

Despite the valuable insights provided, this study has some limitations that should be acknowledged. First, while the survey targeted a large sample of SMEs, the data were self-reported, which may introduce response bias. Respondents may have overestimated or underreported their adoption of AI technologies due to personal biases or social desirability effects. Future studies could benefit from incorporating objective measures, such as actual usage data, to validate self-reported information.

Furthermore, the cross-sectional nature of the study limits the ability to establish causal relationships between the determinants and AI adoption. The findings reflect perceptions and adoption conditions at a single point in time. Longitudinal studies could provide deeper insights into how AI adoption evolves and how organizational capabilities influence sustained implementation.

Although the questionnaire demonstrated acceptable reliability and validity, the use of multiple indicators for each construct resulted in a relatively lengthy instrument. While these indicators were necessary to ensure adequate measurement of the underlying constructs, future studies may develop more parsimonious measurement scales through item reduction techniques and confirmatory validation procedures.

Additionally, the study was limited to Nigerian construction SMEs, and the findings may not be directly applicable to other sectors or countries with different socio-economic contexts. While the results offer valuable insights into the barriers and enablers of AI adoption in Nigeria, they may not fully reflect the unique challenges faced by SMEs in other developing economies. Comparative studies involving multiple countries or industries could provide a broader understanding of AI adoption determinants across different contexts.

Lastly, the study focused on AI adoption within project management functions. While AI technologies have broader applications across the construction industry, the emphasis on project management means that the findings may not fully capture AI adoption in areas such as construction operations, facility management, and lifecycle asset management. Future research could therefore explore AI adoption across the entire construction value chain to provide a more comprehensive understanding of its implementation and impact.

Implications of the study

This study has several important implications for practitioners, policymakers, and future researchers. For practitioners, the findings emphasize the need to prioritize technological infrastructure readiness as a key enabler of AI adoption. Construction SMEs should prioritize investments in reliable internet connectivity, cloud-based project management systems, digital data management platforms, and workforce digital skills development before pursuing more advanced AI applications. Moreover, the resistance to cultural change within the sector needs to be addressed through targeted leadership initiatives that foster a culture of innovation and digital transformation.

For policymakers, the report highlights the need for providing a conducive climate for AI adoption in the construction industry. Government agencies and industry regulators should establish targeted digital transformation programs for construction SMEs, including tax incentives for technology investments, subsidized AI training programs, and partnerships between industry and higher education institutions to strengthen AI-related competencies. In addition, legal frameworks should be created to facilitate the incorporation of AI technologies while addressing possible concerns relating to employment displacement or data privacy.

Finally, the study provides valuable directions for future research. Future studies could explore the long-term effects of AI adoption on construction project performance and firm competitiveness. Additionally, research could investigate how contextual factors - such as national digital readiness or the level of AI-related education - moderate the relationship between AI adoption and firm outcomes. Exploring these areas will deepen our understanding of the factors that influence successful AI adoption in developing economies.

Contributions of the study

This study makes several important contributions to knowledge and practice.

Theoretical Contribution

This study extends existing AI adoption literature by integrating IDT, the TOE framework, and the TAM into a unified analytical framework. The integration of these complementary theories provides a more holistic explanation of AI adoption behavior by simultaneously capturing technological, organizational, environmental, and behavioral influences. The study therefore contributes to the growing body of research advocating multi-theoretical approaches to technology adoption in developing economies.

Practical Contribution

The findings identify technological infrastructure readiness and perceived AI effectiveness as key enablers of adoption, while high implementation costs, cultural resistance, and lack of skilled expertise represent major barriers. These insights provide practical guidance for construction SME managers in prioritizing investments, workforce development initiatives, and digital transformation strategies.

Contextual Contribution

This study contributes empirical evidence from Nigeria, a developing economy where AI adoption remains underexplored. By focusing on SMEs within the Nigerian construction sector, the study provides context-specific insights that extend the applicability of AI adoption theories to developing country settings.

Conclusions

This study investigates the key determinants influencing the adoption of AI among SMEs in Nigeria. The findings reveal that the adoption process is shaped by both enablers and barriers. Technological infrastructure readiness emerged as the most significant enabler of AI adoption, while barriers such as financial limitations, cultural resistance, and a lack of skilled expertise remain the primary challenges hindering the widespread adoption of AI in Nigerian construction SMEs. These findings align with the existing literature, which highlights the importance of digital infrastructure in enabling technology adoption, as well as the significant barriers posed by financial constraints and workforce limitations in developing economies.

For construction SME managers, the study underscores the importance of integrating AI adoption into their organizational strategies. To facilitate AI adoption and overcome the identified barriers, it is crucial to enhance technological infrastructure readiness to support AI implementation. Additionally, providing comprehensive training programs will be essential to upskill the workforce and address the current skills gap. Cultural resistance, which remains a significant barrier, can be mitigated through a gradual and phased implementation of AI technologies, supported by strong leadership that fosters a culture of digital transformation.

For policymakers and industry regulators, the study advocates for creating a supportive ecosystem that encourages AI adoption in the construction sector. This includes promoting infrastructure development to support digital tools and technologies, supporting digital skills training initiatives to equip the workforce with the necessary capabilities, and offering financial incentives to SMEs to alleviate the high costs associated with AI adoption. By fostering an enabling environment, policymakers can help SMEs overcome the financial and infrastructural barriers that currently hinder AI adoption.

In conclusion, the research highlights the critical role of both enablers and barriers in the adoption of AI technologies within Nigeria's construction industry. Future research should explore the long-term effects of AI adoption on the competitiveness and profitability of small and medium construction businesses (SMEs) in Nigeria.

Appendices

QUESTIONNAIRE

Section A: Demographic Information

Please tick (✓) as appropriate

Kindly indicate the nature of projects that you have worked on.

a. ☐ Public Sector b. ☐ Private Sector c. ☐ Both

Please indicate your company area of specialization: a. ☐ Building b. ☐ Building & Civil Engineering c. ☐ Civil engineering d. ☐ Industrial/heavy engineering

What type of construction projects does your firm primarily handle? (Tick all that apply) a. ☐ Residential b. ☐ Commercial c. ☐ Infrastructure d. ☐ Mixed-use (specify) ___________

Kindly indicate your status in the firm: a. ☐ Top Management b. ☐ Middle Management c. ☐ Lower Management d. ☐ Others (specify) ________________

Professional specialization type: a. ☐ Architect b. ☐ Builder c. ☐ Engineer
d. ☐ Estate/Property Manager e. ☐ Land Surveyor f. ☐ Quantity Surveyor
g. ☐ Urban and Town Planners h. ☐ Others (specify) _______________________

Highest level of educational qualification: a. ☐ Certificate b. ☐ ND c. ☐ HND
d. ☐ BSc/BTech e. ☐ PGD f. ☐ MSc g. ☐ PhD h. ☐ Others (specify) ___________

Statutory professional body registration: a. ☐ ARCON b. ☐ CARBON c. ☐ COREN d. ☐ ESVARBON e. ☐ SURCON f. ☐ QSRBN g. ☐ TOPREC h. ☐ Others (specify) __________

Years working in the construction industry: a. ☐ Less than 5 years b. ☐ 5-10 years
c. ☐ 11-15 years d. ☐ 16-20 years e. ☐ Over 20 years

How many years has your firm been operating in the Nigerian construction industry?
a. ☐ Less than 5 years b. ☐ 5-10 years c. ☐ 11-15 years d. ☐ 16-20 years
e. ☐ Over 20 years

Please indicate the number of permanent employees in your firm.

a. ☐ 1-50 employees b. ☐ 51-200 employees c. ☐ 201+ employees

Rate your level of awareness of artificial intelligence (AI) applications in the construction industry.

☐ Not aware b. ☐ Slightly aware c. ☐ Neutral d. ☐ Aware e. ☐ Highly aware

Section B: The extent of AI adoption in construction management (AI-Adopting Firms)

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Please indicate the extent to which you agree that AI tools are currently used for the following functions in your construction projects. (Use a 5-point scale: 1 = Strongly Disagree 2 = Disagree 3 = Neutral 4 = Agree 5 = Strongly Agree)

a. Design & Planning ☐1 ☐2 ☐3 ☐4 ☐5

b. Scheduling ☐1 ☐2 ☐3 ☐4 ☐5

c. Budgeting/Cost Control ☐1 ☐2 ☐3 ☐4 ☐5

d. Quality Control ☐1 ☐2 ☐3 ☐4 ☐5

e. Safety Monitoring ☐1 ☐2 ☐3 ☐4 ☐5

f. Communication/Reporting ☐1 ☐2 ☐3 ☐4 ☐5

Please indicate the extent to which the following Artificial Intelligence (AI) tools are currently utilized in your firm for managing construction projects. (Use a 5-point scale: 1 = Not Utilized 2 = Rarely Utilized 3 = Occasionally Utilized 4 = Frequently Utilized 5 = Extensively Utilized)

a. Machine Learning (e.g., predictive modelling, pattern recognition) ☐1 ☐2 ☐3 ☐4 ☐5

b. Natural Language Processing (e.g., document automation, chatbot assistants) ☐1 ☐2 ☐3 ☐4 ☐5

c. Computer Vision (e.g., site monitoring, defect detection) ☐1 ☐2 ☐3 ☐4 ☐5

d. AI-Driven Scheduling Tools ☐1 ☐2 ☐3 ☐4 ☐5

e. AI-Based Cost Estimation Software ☐1 ☐2 ☐3 ☐4 ☐5

f. Building Information Modelling (BIM) integrated with AI ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

How effective are these AI tools in meeting project management needs? (Rate on a scale of 1-5: 1 = Not effective, 2 = Slightly effective, 3 = Moderately effective, 4 = very effective, 5 = Extremely effective)

a. Machine Learning (e.g., predictive modelling, pattern recognition) ☐1 ☐2 ☐3 ☐4 ☐5

b. Natural Language Processing (e.g., document automation, chatbot assistants) ☐1 ☐2 ☐3 ☐4 ☐5

c. Computer Vision (e.g., site monitoring, defect detection) ☐1 ☐2 ☐3 ☐4 ☐5

d. AI-Driven Scheduling Tools ☐1 ☐2 ☐3 ☐4 ☐5

e. AI-Based Cost Estimation Software ☐1 ☐2 ☐3 ☐4 ☐5

f. Building Information Modelling (BIM) integrated with AI ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

Section C: Enablers of AI adoption

Please indicate the extent to which you agree that the following factors support or facilitate AI adoption in your organization. (Use a 5-point scale: 1 = Strongly Disagree 2 = Disagree 3 = Neutral 4 = Agree 5 = Strongly Agree).

a. Industry Support

i. Industry-driven policies and initiatives ☐1 ☐2 ☐3 ☐4 ☐5

ii. Industry collaboration and partnerships ☐1 ☐2 ☐3 ☐4 ☐5

iii. Availability of industry resources and funding ☐1 ☐2 ☐3 ☐4 ☐5

iv. Industry support for AI adoption ☐1 ☐2 ☐3 ☐4 ☐5

b. Technological Support

i. Availability of advanced technological infrastructure. ☐1 ☐2 ☐3 ☐4 ☐5

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ii. Access to AI tools and platforms ☐1 ☐2 ☐3 ☐4 ☐5

iii. Integration of AI with existing systems ☐1 ☐2 ☐3 ☐4 ☐5

c. Top Management Support

i. Commitment of top management to AI initiatives ☐1 ☐2 ☐3 ☐4 ☐5

ii. Allocation of resources by leadership ☐1 ☐2 ☐3 ☐4 ☐5

iii. Strategic vision for AI adoption ☐1 ☐2 ☐3 ☐4 ☐5

iv. Encouragement and support from executives ☐1 ☐2 ☐3 ☐4 ☐5

d. Workforce Training and Skills

i. Availability of AI-related training programs ☐1 ☐2 ☐3 ☐4 ☐5

ii. Skill development opportunities for employees ☐1 ☐2 ☐3 ☐4 ☐5

iii. Continuous professional development in AI ☐1 ☐2 ☐3 ☐4 ☐5

e. Regulatory & Institutional

i. Institutional policies enabling AI adoption. ☐1 ☐2 ☐3 ☐4 ☐5

ii. Supportive regulatory frameworks for AI ☐1 ☐2 ☐3 ☐4 ☐5

Section D: Barriers to AI Adoption

Please indicate the extent to which you agree that the following are barriers to AI adoption in your organization. (Use a 5-point scale: 1 = Strongly Disagree 2 = Disagree 3 = Neutral 4 = Agree 5 = Strongly Agree)

a. High Implementation Cost

i. The financial investment required for adoption is perceived as excessive. ☐1 ☐2 ☐3 ☐4 ☐5

ii. Limited budgets and resource constraints restrict the ability to implement new systems. ☐1 ☐2 ☐3 ☐4 ☐5

iii. Ongoing operational and maintenance costs are seen as unsustainable. ☐1 ☐2 ☐3 ☐4 ☐5

b. Data Availability & Quality

i. Reliable and high-quality data are often lacking for effective decision-making. ☐1 ☐2 ☐3 ☐4 ☐5

ii. Data access is fragmented, inconsistent, or incomplete across systems ☐1 ☐2 ☐3 ☐4 ☐5

iii. Concerns about data accuracy reduce confidence in its usefulness ☐1 ☐2 ☐3 ☐4 ☐5

c. Technical Complexity & Integration

i. Integrating new technologies with existing infrastructure is technically challenging. ☐1 ☐2 ☐3 ☐4 ☐5

ii. Complex system requirements hinder smooth implementation. ☐1 ☐2 ☐3 ☐4 ☐5

iii. Lack of interoperability between platforms creates additional technical barriers. ☐1 ☐2 ☐3 ☐4 ☐5

d. Lack of Skilled Expertise

i. There is a shortage of staff with the necessary technical knowledge. ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

ii. Limited training opportunities restrict capacity building ☐1 ☐2 ☐3 ☐4 ☐5

iii. Dependence on external expertise increases reliance and vulnerability ☐1 ☐2 ☐3 ☐4 ☐5

e. Resistance to Cultural Change

i. Organizational culture resists new approaches or innovations. ❒1 ❒2 ❒3 ❒4 ❒5

ii. Employees are reluctant to adapt established practices ❒1 ❒2 ❒3 ❒4 ❒5

iii. Fear of uncertainty and loss of control fuels resistance to change ❒1 ❒2 ❒3 ❒4 ❒5

iv. Inadequate digital connectivity, power supply, and systems integration. ❒1 ❒2 ❒3 ❒4 ❒5

Additional Information

Author Contributions

All authors have reviewed the final version to be published and agreed to be accountable for all aspects of the work.

Concept and design: Samuel A. Alara, Peter A. Kuroshi, Iorwuese Anum

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Disclosures

Human subjects: Consent was obtained or waived by all participants in this study. Modibbo Adama University Ethics Review Board issued approval (Ph.D/BUD/22/0532). This study involved minimal-risk human participation (e.g., professional opinions and non-identifiable information). Informed consent was obtained from all participants before data collection. **Animal subjects:** All authors have confirmed that this study did not involve animal subjects or tissue. **Conflicts of interest:** In compliance with the ICMJE uniform disclosure form, all authors declare the following: **Payment/services info:** All authors have declared that no financial support was received from any organization for the submitted work. **Financial relationships:** All authors have declared that they have no financial relationships at present or within the previous three years with any organizations that might have an interest in the submitted work. **Other relationships:** All authors have declared that there are no other relationships or activities that could appear to have influenced the submitted work.

Data Availability Statements

The datasets (and/or code) supporting this study are available from the corresponding author upon reasonable request.

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