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Extent and Pattern of Digital Technology Adoption among Contractors and Consultants in North East Nigeria

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Abstract

Digital technologies can improve coordination, documentation, and control in construction, but evidence on how far they have been adopted in North East Nigeria, a region engaged in post-conflict reconstruction, is limited. This study assessed the extent and pattern of technology adoption among contractor and consultant firms in Adamawa, Bauchi, and Borno States and tested whether adoption differs by firm size. A cross-sectional survey was administered to a proportionate stratified random sample of 187 registered firms drawn from a frame of 350, yielding 149 valid responses (82.4% response rate). Twelve technologies were rated on a five-point scale and analysed with means, standard deviations, rankings, and one-way ANOVA. Overall adoption was moderate ($M = 3.06$, $SD = 0.968$) and fell into three tiers. Foundational tools were most adopted: project management software ($M = 3.64$), mobile applications for site communication ($M = 3.52$), and digital documentation ($M = 3.41$). Cloud collaboration, automated scheduling, cost estimation software, and cross-phase integration were moderate and more variable ($M = 2.97$ to 3.28). Building Information Modelling ($M = 2.84$), drones ($M = 2.71$), IoT sensors ($M = 2.53$), augmented reality ($M = 2.38$), and artificial intelligence ($M = 2.21$) were marginal. Adoption differed significantly by firm size, $F(2, 146) = 13.42$, $p < 0.001$, $\eta^2 = 0.155$, with large firms ($M = 3.81$) well ahead of medium ($M = 3.34$) and small firms ($M = 2.76$). The study recommends staged, low-cost digital upgrading, skills training, and infrastructure and financing support targeted at small firms.

Keywords: technology adoption; digital construction; BIM; firm size; contractors; consultants; North East Nigeria

1.0 Introduction

Digital technologies are reshaping construction through project management software, mobile and cloud tools, Building Information Modelling (BIM), sensing, and artificial intelligence (AI), and their potential to cut errors and rework is well documented (Eastman et al., 2011; Sacks et al., 2020). The evidence from Nigeria, however, points to slow and uneven uptake. Studies report limited use of BIM (Abubakar et al., 2014; Enegbuma et al., 2014;

Onungwa et al., 2017), modest use of information and communication technology (Ibem & Laryea, 2015), and wide barriers to digital technologies generally (Aghimien et al., 2022; Oke, 2024). Most of this work is drawn from southern and central Nigeria.

The North East presents a distinct case. Firms there are delivering large reconstruction programmes in conditions of insecurity and weak infrastructure (Bala et al., 2021), where tools that help coordinate dispersed sites and document work could matter greatly. Yet the extent to which these firms use specific technologies is not known, nor whether use varies by firm size, although small firms dominate the industry. This paper addresses that gap, covering contractors and consultants together.

The study answered two questions: (i) to what extent have construction firms in Adamawa, Bauchi, and Borno States adopted digital technologies, and which technologies lead and lag? and (ii) does technology adoption differ among small, medium, and large firms?

2.0 Literature Review

2.1 Technologies in construction

Foundational digital tools include project management software, mobile applications for site communication, digital documentation, and cloud-based collaboration platforms. More advanced technologies include BIM, drones for surveying and monitoring, Internet of Things (IoT) sensors for equipment tracking (Ghosh et al., 2020), augmented reality, and AI for planning and prediction (Sacks et al., 2020). BIM in particular is widely reported to reduce design errors, rework, and coordination time (Eastman et al., 2011).

2.2 Adoption patterns and barriers in developing countries

Studies in developing economies report that adoption concentrates in low-cost, easy-to-use tools, while advanced technologies face cost, skills, and infrastructure barriers (Aghimien et al., 2022; Olanrewaju et al., 2020). In Nigeria, the barriers to BIM include cost, lack of skills, and weak demand from clients (Abubakar et al., 2014; Enegbuma et al., 2014; Onungwa et al., 2017), and recent work finds that AI adoption faces a severe combination of cost, data, and skills barriers (Acheampong et al., 2025). Training and skills development have been identified as critical to digital construction in Nigeria (Ibrahim, 2024).

2.3 Theoretical perspectives

Two frameworks guide interpretation. Diffusion of Innovation Theory explains adoption through five attributes of an innovation: relative advantage, compatibility, complexity, trialability, and observability (Rogers, 2003). The Technology–Organisation–Environment (TOE) framework explains adoption through technological characteristics, organisational capacity, and environmental conditions (Tornatzky & Fleischer, 1990). Combined with the Resource-Based View, which links capability to resource endowment (Barney, 1991), they predict that simple, low-cost tools will be adopted first and that larger firms, with greater organisational capacity, will adopt more. The study therefore tested the hypothesis that mean technology adoption differs significantly across small, medium, and large firms.

3.0 Methodology

A quantitative, cross-sectional survey design was adopted within a positivist paradigm (Saunders et al., 2019; Creswell & Creswell, 2018). The study covered Adamawa, Bauchi, and Borno States, three states of the North East geopolitical zone that are the focus of post-conflict reconstruction (Bala et al., 2021). The target population was all registered contractor and consultant firms operating in the three states. A sampling frame of 350 firms (Adamawa 77, Bauchi 142, Borno 131) was compiled from the registers appropriate to each category: for contractors, the membership directories of the Federation of Construction Industry, the registers of the Bureau of Public Procurement and state procurement agencies, and the contractor lists of state ministries of works; for consultants, the registers of the Council for the Regulation of Engineering in Nigeria, the Architects Registration Council of Nigeria, the Quantity Surveyors Registration

Board of Nigeria, and the Nigerian Institute of Quantity Surveyors; and, for building contractors and consultancies, the Nigerian Institute of Building and the Council of Registered Builders of Nigeria. Entries were merged, de-duplicated and verified against the Corporate Affairs Commission register.

Proportionate stratified random sampling was used, with states as strata and simple random selection within each state. Yamane's formula (Uakarn et al., 2021) gave a sample of 187 firms, allocated as 41 (Adamawa), 76 (Bauchi), and 70 (Borno). One senior key informant per firm (managing director, general manager, principal partner, head of practice, project manager, or lead consultant) completed the questionnaire (Kumar et al., 1993). The questionnaire was administered electronically by email and an online form, with two reminders and telephone follow-up over six months. In all, 154 questionnaires were returned (82.4%), and 149 were valid after multivariate outliers were removed. Table 1 gives the profile of the valid sample.

Table 1: Profile of Respondent Firms (N = 149)

Characteristic	Category	N	%
Firm type	Contractor	83	55.7
	Consultant	66	44.3
Firm size (SMEDAN, 2019)	Small (< 50 employees)	87	58.4
	Medium (50–199 employees)	42	28.2
	Large (≥ 200 employees)	20	13.4
State	Adamawa	30	20.1
	Bauchi	63	42.3
	Borno	56	37.6

Source: Field survey (2026).

The instrument was a structured questionnaire. Section C measured technology adoption with 12 items covering project management software, mobile applications for site communication, digital documentation systems, cloud-based collaboration tools, automated scheduling software, cost estimation software, integration of technology across project phases, BIM, drones, IoT sensors, augmented reality, and AI for project planning. Each was rated on a five-point scale of extent of use (1 = lowest extent, 5 = highest extent). Items were adapted from Sacks et al. (2010), Olanrewaju et al. (2020), and Nnaji and Karakhan (2020). Content validity was established by a panel of five experts, and a pilot with 30 firms excluded from the main sample returned Cronbach's alpha values of 0.824 to 0.901. In the main study, the technology adoption scale was reliable ($\alpha = 0.908$; composite reliability = 0.923; AVE = 0.597; Hair et al., 2021). Means, standard deviations, and ranks were computed, and one-way ANOVA with Tukey's HSD compared adoption across size categories, with η^2 as the effect size. Participation was voluntary, consent was informed, and responses were anonymous.

4.0 Results

4.1 Extent of technology adoption

Table 2 shows that overall adoption was moderate (M = 3.06, SD = 0.968), at the lower edge of the moderate range, and the technologies fall into three tiers.

The first tier comprises project management software (M = 3.64), mobile applications for site communication (M = 3.52), and digital documentation systems (M = 3.41). The second tier comprises cloud-based collaboration tools (M = 3.28), automated scheduling software (M = 3.15), cost estimation software (M = 3.09), and integration of technology across project phases (M = 2.97); these have higher standard deviations (1.189 to 1.254), indicating that some firms use them systematically and others hardly at all. The third tier comprises BIM (M = 2.84), drones (M = 2.71), IoT sensors (M = 2.53), augmented reality (M = 2.38), and AI for project planning (M = 2.21), the lowest score in the whole instrument.

Table 2: Extent of Technology Adoption (N = 149)

Technology	Mean	SD	Rank	Adoption level
Project management software	3.64	1.087	1	Moderate-high
Mobile applications for site communication	3.52	1.124	2	Moderate-high
Digital documentation systems	3.41	1.156	3	Moderate
Cloud-based collaboration tools	3.28	1.189	4	Moderate
Automated scheduling software	3.15	1.203	5	Moderate
Cost estimation software	3.09	1.227	6	Moderate
Integration of technology across project phases	2.97	1.254	7	Moderate-low
Building Information Modelling (BIM)	2.84	1.298	8	Low-moderate
Drones for site monitoring and surveying	2.71	1.326	9	Low
IoT sensors for equipment tracking	2.53	1.347	10	Low
Augmented reality for visualization	2.38	1.289	11	Low
AI for project planning	2.21	1.234	12	Very low
Overall composite	3.06	0.968	–	Moderate

Source: Field survey (2026). Scale: 1 = lowest extent, 5 = highest extent.

4.2 Technology adoption by firm size

Adoption rose with firm size (Table 3). Large firms recorded a mean of 3.81 (SD = 0.723), medium firms 3.34 (SD = 0.854), and small firms 2.76 (SD = 0.987). The ANOVA showed a significant difference, $F(2, 146) = 13.42$, $p < 0.001$, $\eta^2 = 0.155$, a large effect. Tukey's HSD tests showed that large firms adopted significantly more than medium firms ($p < 0.01$) and small firms ($p < 0.001$), and medium firms significantly more than small firms ($p < 0.01$). The hypothesis was supported. The effect of size on technology adoption ($\eta^2 = 0.155$) was larger than its effect on lean practice adoption in the same sample ($\eta^2 = 0.119$).

Table 3: Technology Adoption by Firm Size

Firm size	N	Mean	SD	Adoption level
Small (< 50 employees)	87	2.76	0.987	Low-moderate
Medium (50–199 employees)	42	3.34	0.854	Moderate
Large (≥ 200 employees)	20	3.81	0.723	High
All firms	149	3.06	0.968	Moderate

Source: Field survey (2026). ANOVA: $F(2, 146) = 13.42$, $p < 0.001$, $\eta^2 = 0.155$.

5.0 Discussion

5.1 A tiered digital landscape

The three tiers match what Diffusion of Innovation Theory predicts (Rogers, 2003). Project management software, mobile applications, and digital documentation are low in cost, easy to use, compatible with existing routines, and show benefits quickly, so they have spread. BIM, drones, IoT sensors, augmented reality, and AI score lower on relative advantage that is visible in the short term, and higher on complexity and the expertise required, so they remain marginal. The pattern agrees with earlier Nigerian and developing-country evidence (Aghimien et al., 2022; Olanrewaju et al., 2020; Onungwa et al., 2017). The high standard deviations in the second and third tiers show that the averages conceal a gap between a few capable firms and many firms that have not started.

5.2 Barriers through the TOE lens

The TOE framework (Tornatzky & Fleischer, 1990) helps to explain what holds back the advanced tools. Technologically, they carry high acquisition, training, and maintenance costs. Organisationally, skills gaps and cautious leadership limit the capacity to absorb them (Ibrahim, 2024). Environmentally, unreliable power and internet connectivity, which are particular problems in parts of the North East, reduce the value of cloud, IoT, and sensing tools. The very low score for AI is consistent with the cost, data, and skills barriers reported for Nigerian firms (Acheampong et al., 2025). The study did not measure these barriers directly, so they are offered as plausible explanations to be tested.

5.3 Firm size and the digital divide

Large firms are far ahead, and the effect of size is larger for technology than for lean practice. This is what the Resource-Based View would predict, since digital tools require capital, skills, and infrastructure to a greater degree than behavioural practices (Barney, 1991). The small-firm mean of 2.76 suggests that the typical small firm relies mainly on basic communication tools with little use of advanced construction technologies, in line with studies of Nigerian construction SMEs (Olanrewaju et al., 2020). Because small firms form 58.4% of the sample, the digital divide has implications for the sector as a whole.

5.4 Foregone gains

The least adopted technologies are those with the strongest evidence of efficiency gains. BIM is associated with fewer design errors and less rework (Eastman et al., 2011), and AI and sensing tools target the cost overruns and quality problems that firms in the region report. Their low adoption therefore represents unrealised potential and not a lack of relevance.

6.0 Conclusion and Recommendations

Technology adoption among contractors and consultants in Adamawa, Bauchi, and Borno States is moderate overall but concentrated in foundational tools, with BIM, drones, IoT, augmented reality, and AI at marginal levels. Adoption

increases significantly with firm size. The study provides one of the first firm-level, tool-by-tool profiles of digital adoption in the North East.

• Firms, particularly small ones, should deepen use of the foundational tools (project management software, mobile applications, cloud collaboration) before attempting advanced technologies, and adopt BIM and drones through pilot projects.

• Professional bodies, universities, and training providers should offer affordable training in BIM and data-driven project control, since skills are a recurrent barrier.

• Government and development agencies operating in the region should support power and internet infrastructure and consider financing or tax incentives that make digital tools affordable to small firms.

• Public clients could specify digital deliverables, such as electronic documentation and BIM on suitable projects, in tenders, to create demand.

The study is cross-sectional, rests on one informant per firm, and is limited to registered firms in three states, so the findings should not be generalised to the rest of the zone. Future research should measure adoption barriers directly, compare contractors with consultants, and track adoption over time.

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