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RESEARCH ARTICLE

IoT and Machine Learning for Lifecycle Cost Optimization in Nigerian Commercial High-Rise Buildings

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ABSTRACT

Commercial high-rise buildings in Nigeria's major urban centres, Lagos and Abuja, face a compounding operational crisis: chronic grid instability, entrenched diesel generator dependency, and reactive maintenance paradigms that inflate lifecycle costs well beyond benchmarks in developed economies. Nigeria loses approximately US$985 million annually to power outages. Although Internet of Things (IoT) sensor networks and machine learning (ML) have demonstrated global potential to cut operational costs by 17.6% and maintenance spend by 13.2%, no empirically validated framework exists for their deployment in sub-Saharan Africa's commercial real estate markets. This study administered a structured six-section questionnaire to 50 facility managers, property managers, building owners, and technology practitioners across Lagos and Abuja, using a convergent mixed-methods design analysed via descriptive statistics, Cronbach's alpha, Spearman correlation, and Kruskal-Wallis tests. Findings show 58% of surveyed buildings rely on reactive or schedule-based maintenance, with only 10% practising predictive strategies. A critical willingness-capability gap emerged: practitioners express high investment willingness given demonstrated ROI (mean 4.20/5) yet report low ML familiarity (2.90/5) and inadequately skilled personnel (2.98/5). Contrary to global literature, economic and institutional barriers, high upfront cost (4.42/5), absent incentives (4.38/5), and weak policy support (4.38/5) outrank technical constraints as the dominant adoption impediments. Power outages generated the highest IoT-section score (4.34/5), confirming a Diesel-Grid Paradox as a central operational challenge, while lifecycle cost importance recorded the highest overall rating (4.64/5). Effective IoT-ML adoption in Nigerian commercial high-rises will require fiscal reform, regulatory strengthening, and demonstration-based evidence.

Keywords: *IoT; Machine learning; Lifecycle cost; high-rise buildings; Emerging economies; Facility management*

1. INTRODUCTION

The global built environment is undergoing rapid transformation driven by urbanisation, technological innovation, and increasing demands for sustainability. As cities expand and building systems become more complex, attention has shifted from merely constructing assets to ensuring that they operate efficiently throughout their lifecycle. This shift is particularly important because operational and maintenance expenditures often exceed initial construction costs over the lifespan of a building.

Buildings account for a substantial share of global energy consumption and carbon emissions, making them a critical focus of sustainability and efficiency initiatives. According to international estimates, the building sector contributes approximately 36–40% of global energy use and nearly 38% of carbon dioxide emissions. (International Energy Agency [IEA], 2023; UN Environment Programme, 2022; European Commission, 2025).

At the same time, urban populations continue to grow, with sub-Saharan Africa expected to experience some of the fastest rates of urban expansion in the coming decades. (UN-Habitat, 2022; World Economic Forum, 2023). Within this context, commercial high-rise buildings represent some of the most resource-intensive components of the urban environment, requiring significant investments in energy, maintenance, and operational management. (Flanagan & Jewell, 2021; Atkin & Brooks, 2021).

Lifecycle Costing (LCC)provides a framework for understanding and managing these long-term expenditures. (ISO 15686-5, 2017; Flanagan & Jewell, 2021). Rather than focusing solely on initial capital costs, LCC considers all costs associated with a building throughout its operational life. Research has consistently shown that operational and maintenance activities account for between 70% and 80% of a building's total lifecycle expenditure. Consequently, strategies that improve operational efficiency can generate substantial financial benefits for building owners and managers. Popovychenko et al. (2023) demonstrate through a comparative analysis of international LCC practice that the operation and maintenance of an office building over a 2–3-decade horizon may cost several times more than its initial capital outlay, yet in developing countries, attention remains disproportionately focused on initial capital investments rather than on cumulative operational costs. The concept of Whole Life Appraisal (WLA), elaborated by Popovychenko et al. (2023) following the foundational work of Flanagan, Jewell and Norman (2005), constitutes a systematic consideration of all relevant costs, revenues, and outcomes connected with asset acquisition and ownership across its physical, economic, functional, and operational life.

Advances associated with Industry 4.0 have created new opportunities for improving building performance through the integration of digital technologies. Internet of Things (IoT) sensor networks enable continuous monitoring of building systems, while machine learning algorithms can analyse large volumes of operational data to identify patterns, predict equipment failures, optimise energy consumption, and support informed maintenance decisions. In many developed economies, these technologies have become integral components of smart building management systems, delivering measurable reductions in operational costs, maintenance expenditure, and energy consumption (Nižetić et al., 2020; Ancillai et al., 2023). Emedo et al. (2025), in a systematic narrative review of 2016–2024 literature spanning property valuation, predictive maintenance, and smart building operations, establish that AI-driven systems achieve average operational cost reductions of 17.6%, maintenance savings of 13.2%, and energy savings of 14%, performance improvements that position intelligent building management as one of the most financially compelling asset management strategies available. The

Memoori Research Group (2024) projects that the number of IoT-connected devices in commercial buildings globally will reach 4.1 billion by 2030, a scale of deployment that would fundamentally transform the built environment's capacity for predictive intelligence. Yet this digital transformation has remained profoundly uneven across geographic and economic lines.

Despite these developments, the adoption of IoT and machine learning technologies within many emerging economies remains limited. In Nigeria, the management of commercial high-rise buildings is complicated by unreliable electricity supply, heavy dependence on diesel generators, rising maintenance costs, inflationary pressures, and aging infrastructure. These conditions increase operational risks and place significant financial burdens on property owners and facility managers.

The challenge is particularly evident in Lagos and Abuja, Nigeria's two largest commercial real estate markets. Frequent power outages, inadequate maintenance documentation, and limited adoption of digital technologies have constrained the ability of building operators to implement predictive maintenance practices. Although some high-end commercial buildings have introduced Building Management Systems (BMS), these systems often function primarily as monitoring tools rather than intelligent decision-support platforms capable of generating predictive insights. (Ogunbayo et al., 2022; NIESV, 2025; Karnilius et al., 2024). Ogunbayo, Aigbavboa, Thwala and Akinradewo (2022), in a Delphi study of maintenance budget management in the Nigerian built environment, document the absence of standardised maintenance management structures, a structural deficit that directly prevents the financial planning and data recording necessary for lifecycle cost optimisation.

The scale of Nigeria's energy infrastructure deficit further compounds these operational pressures. Orumwense, Ighodaro and Abo-Al-Ez (2021) document that approximately US$985 million (376 billion naira) is lost annually due to constant power outages, and that Nigeria's per capita electricity consumption of 0.03 kW places it among the lowest-ranked nations globally, a figure dwarfed by comparable developing economies such as Egypt (0.27 kW) and Iraq (0.42 kW). Most large companies operating in Nigeria's commercial centres have resorted to running generators for 100% of their energy requirements, pushing production costs 10–20% higher than comparable neighbouring countries (Orumwense et al., 2021). This dual-power reality exponentially accelerates the degradation of high-value HVAC systems, lifts, and electrical infrastructure, inflating lifecycle costs far beyond the projections of conventional asset management models (Orumwense et al., 2021; Ebiloma et al., 2023).

Evidence from commercial real estate research in Lagos corroborates the intensity of energy-related operational pressure. Oladokun and Shiyanbola (2021), in a study of 95 estate surveying firms managing office buildings in Lagos, found that energy-cost-reduction features attracted the highest demand rating (mean 3.44/4.0) among all sustainable building attributes, with cost saving identified as the primary driver of sustainable feature demand (mean 3.79/4.0), a pattern directly attributable to the epileptic nature of public power supply and the consequent burden of generator operations. Yet occupancy sensors, the most basic prerequisite for IoT-driven demand management, were available in only 3.7% of buildings, confirming this study's finding of near-zero active IoT penetration.

Historically, facility management across Nigeria's commercial property sector has been governed by reactive strategies or time-based scheduled preventive maintenance, generating either costly over-maintenance or chronic underestimation of early failure indicators (Atkin & Brooks, 2021; Ebiloma et al., 2023). Ebiloma, Aigbavboa and Anumba (2023), in a study of digital twin maintenance management readiness in Nigerian health facilities, document a low level of awareness of Industry 4.0 tools in the management of constructed facilities in Nigeria, attributing this to inadequate maintenance documentation. While some Grade-A building owners have invested in Building Automation Systems (BAS) or Building Management Systems (BMS), these platforms have overwhelmingly operated as passive monitoring tools, their limited impact attributable to poor interoperability with legacy infrastructure, fragmented procurement, and a profound shortage of specialised technical expertise (Maqbool et al., 2023; NIESV, 2025). These challenges echo findings from the broader Nigerian digital transformation literature: Ojo, Oyetunji and Oyetunji (2018) identified rapid technological change, inadequate staff competencies, low internet connectivity, and high hardware costs as the most salient barriers to ICT deployment in Nigerian real estate practice. Similarly, Abasilim and Esisio (2025) document that 65% of Nigerian public agencies struggle with inadequate digital infrastructure and nearly 40% of government workers lack the digital literacy needed for effective technology utilisation.

On the global research frontier, the integration of Building Information Modelling (BIM) with lifecycle cost analysis has matured into a recognised methodology for dynamic cost management. Jafary et al. (2025) propose a BIM-CMMS framework for dynamic depreciation estimation through maintenance management integration, while Valinejadshoubi et al. (2024) demonstrate that early BIM-LCCA integration enables comprehensive economic assessments reflecting actual long-term financial implications of design choices. Machine learning algorithms, including Random Forest classifiers, Support Vector Machines (SVM), Long Short-Term Memory (LSTM) networks, and reinforcement learning architectures, have demonstrated measurable capacity to predict equipment failure, optimise energy consumption, and reduce unplanned maintenance expenditure in controlled environments (Aboelmagd, 2024; Scaife, 2024). Bouabdallaoui et al. (2021), in a landmark ML-based predictive maintenance framework validated on HVAC systems, establish a five-step predictive maintenance pathway: data collection, processing, model development, fault notification, and model improvement, confirming the technical viability of IoT-ML integration for building facilities. Anastasiadou et al. (2022), in a PRISMA-based systematic review of 35 studies, establish that ML approaches can effectively automate buildings' energy performance evaluation and predict energy-efficient retrofit measures.

Three structural barriers have consistently prevented translation of these global advances to the Nigerian market. Technically, intermittent grid supply, poor broadband connectivity, high-humidity tropical conditions, and voltage spikes distort sensor data and degrade ML training dataset reliability (Aboelmagd, 2024; Karnilius et al., 2024). Economically, high upfront capital expenditure compounded by Naira depreciation, double-digit inflation, and restricted access to long-term project finance has rendered the ROI case for smart building technology opaque for most Nigerian developers (Ogunbayo et al., 2022; Olukotun & Aniala, 2026). Institutionally, the Nigerian Building Energy Efficiency Code (BEEC) remains aspirational in enforcement terms, with limited inspectorate capacity and no sector-specific mandate for predictive maintenance adoption (BEEC, 2024; Ancillai et al., 2023). This research proposes that the systematic integration of IoT sensor networks and machine learning algorithms can effectively optimise the lifecycle costs of commercial high-rise buildings in Nigeria, delivering a financially viable and operationally resilient transition from reactive to predictive maintenance within the distinct constraints of an emerging economy.

Although the benefits of IoT-enabled building management and machine learning-based predictive maintenance have been extensively documented in developed economies, empirical evidence from emerging economies remains limited. Existing studies have largely focused on the technical capabilities of these technologies, including energy optimisation, equipment fault detection, and automated maintenance scheduling. However, relatively little attention has been given to the institutional, economic, and infrastructural realities that influence their adoption in developing countries.

In the Nigerian context, available studies have primarily examined building maintenance challenges, sustainable building features, digital transformation, and facility management practices independently. Few studies have explored how IoT sensor networks and machine learning technologies can be integrated into commercial building operations to support lifecycle cost optimisation. More importantly, there is limited empirical evidence on stakeholder readiness, adoption barriers, investment willingness, and the practical conditions necessary for successful implementation.

This knowledge gap is particularly significant given the unique operating environment of Nigerian commercial high-rise buildings. Frequent power outages, dependence on alternative energy sources, limited technical expertise, weak regulatory enforcement, and constrained access to finance create conditions that differ substantially from those reported in developed countries where most smart-building research has been conducted. The absence of locally generated evidence has also contributed to uncertainty among property owners and facility managers regarding the economic viability of IoT and machine learning investments.

This study contributes to both theory and practice in four important ways. First, it provides one of the earliest empirical assessments of IoT sensor network and machine learning adoption within Nigeria's commercial high-rise building sector. Second, it extends the lifecycle costing and whole-life appraisal literature by examining how digital technologies can support long-term cost optimisation in emerging-market environments. Third, it identifies and ranks the technical, economic, and institutional barriers that influence technology adoption decisions among building stakeholders. Finally, it provides practical recommendations for facility managers, investors, technology providers, and policymakers seeking to promote data-driven building management and sustainable asset performance.

By situating global smart-building innovations within the realities of the Nigerian commercial property market, the study offers valuable insights into how emerging economies can leverage digital technologies to improve operational efficiency, reduce lifecycle costs, and enhance the long-term sustainability of commercial real estate assets.

2. MATERIALS AND METHODS

This study adopted an explanatory sequential mixed-methods design to investigate the adoption, barriers, and lifecycle cost implications of IoT sensor networks and machine learning technologies in commercial high-rise buildings across Nigeria. Under this design, quantitative data were collected and analysed first, with quantitative findings subsequently used to shape the interpretation of contextual data (Creswell, 2014). The study was guided by the pragmatist research philosophy, which emphasizes the use of methods that best address the research objectives rather than strict adherence to a single methodological tradition. This philosophical stance is particularly suitable for applied research involving technological adoption and organisational decision-making, where both numerical evidence and contextual understanding are important (Creswell, 2014; Yin, 2018).

The research was conducted in Lagos and Abuja, Nigeria's two most significant commercial real estate markets. Lagos and Abuja were selected as the study locations because they represent Nigeria's two most important commercial office markets and host a substantial concentration of the country's premium office developments. Lagos remains the dominant commercial hub, driven by rapid urbanisation, corporate headquarters, multinational investment, and sustained demand for office accommodation, while Abuja serves as the nation's administrative capital and a major centre for government, diplomatic, and professional services (UN-Habitat, 2022; Agusto & Co., 2024). Recent industry analyses identify Lagos and Abuja as the primary hubs of Nigeria's formal office-space market, with Lagos accounting for the largest concentration of Grade A office developments and Abuja serving as the country's second-largest office market. Nigeria has taken important steps toward improving energy performance within the built environment through the development of the Nigerian Building Energy Efficiency Code (BEEC). The code establishes minimum energy-efficiency requirements for buildings and was developed through a collaborative policy process involving government agencies and international development partners. Studies indicate that effective implementation of the BEEC could significantly reduce energy consumption in buildings while supporting broader sustainability objectives. Existing research has demonstrated the technical effectiveness of IoT-enabled monitoring systems, predictive maintenance frameworks, and machine learning applications in improving energy efficiency, reducing equipment downtime, and optimising operational performance in buildings (Nižetić et al., 2020; Bouabdallaoui et al., 2021; Anastasiadou et al., 2022; Scaife, 2024). However, much of this evidence originates from developed economies characterised by reliable energy infrastructure, mature regulatory frameworks, and higher levels of digital readiness. Consequently, there remains limited empirical evidence regarding how these technologies can be adopted and implemented effectively within emerging economies such as Nigeria, where infrastructure deficits, financing constraints, and institutional barriers present unique challenges.

The target population comprised professionals directly involved in the management, ownership, operation, and deployment of technologies within commercial high-rise buildings. Participants included facility managers, property managers, building owners, developers, and technology practitioners with experience in building automation, IoT systems, or related digital technologies.

The study adopted a convergent mixed-methods design, combining quantitative and qualitative approaches to provide a comprehensive understanding of IoT and machine learning adoption within commercial high-rise buildings. Mixed-methods research is particularly useful when investigating complex real-world phenomena that require both statistical evidence and contextual interpretation (Creswell, 2014; Patton, 2002).

Purposive sampling was employed because the study required respondents with specialised knowledge of building operations, maintenance management, and digital building technologies. This approach is appropriate where information-rich cases are required to address specific research objectives (Patton, 2002).

Questionnaire items were developed from themes identified in previous studies on smart buildings, predictive maintenance, lifecycle costing, and digital transformation in the built environment (Nižetić et al., 2020; Bouabdallaoui et al., 2021; Aboelmagd, 2024; Emedo et al., 2025).

Internal consistency was assessed using Cronbach's alpha. Reliability coefficients were interpreted according to established guidelines, with values above 0.70 considered acceptable for exploratory and applied research (Nunnally, 1978; George & Mallery, 2019).

Because the majority of variables were measured using ordinal Likert-scale data and the sample size was relatively modest, non-parametric statistical techniques were considered most appropriate (Field, 2018). Spearman's rank-order correlation was used to examine associations between variables (Spearman, 1904), while the Kruskal-Wallis H test was employed to assess differences among respondent groups (Kruskal & Wallis, 1952).

The study was exploratory in nature and targeted a specialised population of professionals involved in commercial high-rise building operations. Similar studies investigating technology adoption within specialised professional groups have successfully employed comparable sample sizes where respondents possess substantial domain expertise (Patton, 2002; Yin, 2018).

A total of 50 respondents participated in the study. The sample consisted of facility managers (42%), property managers (30%), building owners and developers (20%), and IoT technology vendors (8%). Although relatively modest in size, the sample was considered adequate for the exploratory nature of the study and appropriate for the non-parametric statistical techniques employed in the analysis. (Ebiloma et al., 2023; Olukotun & Aniala, 2026). Participation was voluntary and fully anonymised, with all respondents providing informed consent in accordance with the Nigeria Data Protection Act (NDPA, 2023).

Data were collected using a structured six-section self-administered questionnaire designed for this study and aligned with the research objectives, informed by validated instruments from comparable studies on IoT adoption barriers, ML familiarity, and lifecycle cost perceptions (Aboelmagd, 2024; Maqbool et al., 2023; Emedo et al., 2025). Section A collected respondent and building profile data. Section B assessed maintenance practices and costs. Section C measured IoT awareness and current adoption. Section D evaluated ML/AI familiarity, confidence, and investment willingness. Section E assessed barrier severity across technical, economic, and institutional sub-dimensions. Section F evaluated lifecycle cost perceptions and future investment outlook. Likert-scale items used a standardised 1–5 response format (1 = Not at all/Not a barrier; 5 = Extremely/Major barrier), consistent with the approach adopted by Nižetić et al. (2020) and Jafary et al. (2025). The questionnaire was administered via a structured Google Form through professional networks including the Nigerian Institution of Estate Surveyors and Valuers (NIESV) and the Abuja Chamber of Commerce.

Quantitative data were analysed using descriptive statistics (mean, standard deviation, frequency distributions), Cronbach's alpha reliability assessment with George and Mallery's (2019) interpretive criteria (Excellent ≥ 0.90; Good ≥ 0.80; Acceptable ≥ 0.70; Poor ≥ 0.60) and Nunnally's (1978) minimum threshold of $\alpha \geq 0.70$, Spearman's rank-order correlation for ordinal variable associations (Field, 2018), and Kruskal-Wallis H tests for group comparisons across role, city, and BMS status categories (Kruskal & Wallis, 1952). Statistical analyses were conducted using Python 3 (scipy, numpy libraries). Open-ended responses were analysed thematically following Braun and Clarke's (2006) six-phase framework.

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3. RESULTS AND DISCUSSION

Sample Profile and Building Characteristics

A total of 50 valid responses were obtained from professionals involved in the management and operation of commercial high-rise buildings. Facility managers constituted the largest respondent group (42%), followed by property managers (30%), building owners and developers (20%), and IoT technology vendors (8%). Geographically, the majority of respondents were based in Lagos (70%), while the remaining 30% were located in Abuja.

Most respondents managed buildings between 10 and 14 storeys (66%), with the remaining 34% overseeing buildings ranging from 15 to 19 storeys. In terms of digital infrastructure, only 28% of respondents reported having a fully operational Building Management System (BMS), while 36% indicated partial implementation and another 36% reported having no BMS in place. The findings suggest that although some degree of digital infrastructure exists within Nigeria's commercial high-rise sector, comprehensive building automation remains relatively limited. This provides an important context for understanding subsequent findings relating to IoT and machine learning adoption.

Table 1. Sample profile — professional role, city, building characteristics, and maintenance strategy (n = 50)

Variable	Category	n	%
Professional Role	Facility manager	21	42.0
	Property manager	15	30.0
	Building owner/developer	10	20.0
	IoT Vendor	4	8.0

Variable	Category	n	%
City	Lagos	35	70.0
	Abuja	15	30.0
Building Storeys	10–14	33	66.0
	15–19	17	34.0
BMS Status	Yes, fully operational	14	28.0
	Yes, partial	18	36.0
	No BMS	18	36.0
Maintenance Strategy	Scheduled	17	34.0
	Reactive	12	24.0
	Combination	10	20.0
	Condition-based	6	12.0
	Predictive	5	10.0

Maintenance Practices and Costs

Scheduled maintenance was the dominant strategy (n = 17, 34%), followed by reactive/breakdown maintenance (n = 12, 24%), a combination approach (n = 10, 20%), condition-based (n = 6, 12%), and predictive (n = 5, 10%). The combined prevalence of reactive and scheduled strategies is 58%, confirming the persistence of non-predictive maintenance paradigms (Ebiloma et al., 2023; NIESV, 2025). Mean maintenance satisfaction was 3.28/5 (SD = 1.11). The mean financial impact of unplanned failures was 4.0/5 (SD = 0.95). Mean cost estimation accuracy was 3.36/5 (SD = 1.10), reflecting weak financial data infrastructure consistent with Ogunbayo et al. (2022) and with Popovychenko et al.'s (2023) identification of data standardisation deficits as a central obstacle to WLA implementation in developing economies. Maintenance expenditure as a proportion of total OPEX was predominantly 10–20% (38%) and 21–30% (32%), with 28% of buildings reporting maintenance costs exceeding 30% of operational budgets.

IoT Awareness and Adoption

Mean IoT familiarity among respondents was 3.40/5 (SD = 1.14). The most commonly deployed IoT technologies were passive security systems, CCTV, and fire detection — while active performance-monitoring technologies such as energy sub-metering, HVAC sensors, and vibration sensors showed substantially lower penetration, consistent with the passive-to-active adoption gradient documented in the smart building literature (Emedo et al., 2025; Aboelmagd, 2024). Mean sensor data utilisation in maintenance decision-making was 3.14/5 (SD = 1.37). Mean internet reliability was rated 3.44/5 (SD = 0.91), validating the connectivity barrier documented by Maqbool et al. (2023). The mean impact of power supply outages on building sensor systems was 4.34/5 (SD = 0.69), the highest-rated item in Section C, confirming the Diesel-Grid Paradox as a lived operational reality. Thirty percent of respondents reported no structured sensor data storage.

Machine Learning Familiarity and Predictive Maintenance

Mean ML familiarity was 2.90/5 (SD = 1.33), meaningfully lower than IoT familiarity (3.40/5) and reflecting a significant awareness gap. Cronbach's alpha for the Section D ML scale was $\alpha = 0.907$ (Excellent per George & Mallery, 2019). Only 13 respondents (26%) reported currently using any ML or AI tool in building operations; 24% were actively considering adoption; 38% had no adoption plans. Despite this awareness gap, mean willingness to invest given a demonstrated ROI was 4.20/5 (SD = 0.73), revealing a substantial willingness-capability gap. Mean ML confidence for cost reduction was 3.82/5 (SD = 0.87). Mean skills adequacy was rated 2.98/5 (SD = 0.94), confirming a critical human capital deficit consistent with Maqbool et al. (2023). The preferred ROI period was 3–4 years (42%), followed by 1–2 years (28%).

Table 2. Descriptive statistics — key Likert-scale items (n = 50)

Variable	Mean	SD	Interpretation
IoT Familiarity	3.40	1.14	Moderate
Sensor Data Use in Decisions	3.14	1.37	Below optimal
Internet Reliability	3.44	0.91	Moderate; below threshold
Power Outage Impact	4.34	0.69	Critical — highest C-section score
ML Familiarity	2.90	1.33	Low — awareness gap confirmed
ML Cost-Reduction Confidence	3.82	0.87	Moderate-high
Willingness to Invest (given ROI)	4.20	0.73	High — willingness-capability gap
Skills Adequacy	2.98	0.94	Low — human capital deficit
LCC Importance	4.64	0.48	Very high — financial motivation confirmed.
ML LCC Reduction Potential	4.20	0.64	High
Likelihood of IoT Investment (3yr)	3.58	1.11	Moderate — contingent on evidence.

Adoption Barriers

All 16 barrier items across the three sub-dimensions achieved mean scores above 3.50/5. The highest-ranked barrier was High Upfront Installation Cost (Mean = 4.42, SD = 0.50), followed by No Government Incentives (Mean = 4.38, SD = 0.53) and Lack of Policy Support (Mean = 4.38, SD = 0.49). Power Grid Instability (Mean = 4.34, SD = 0.72) was the highest technical barrier. Regulatory supportiveness received a mean score of 2.52/5 (SD = 0.97), the lowest-rated item in the entire study. The results demonstrate that economic and institutional constraints are perceived as more severe than purely technical challenges. This finding differs from much of the international smart-building literature, where technical issues such as interoperability, cybersecurity, and data quality frequently dominate adoption discussions.

When respondents were asked to identify the single most limiting factor affecting implementation, infrastructure-related challenges, particularly unreliable electricity supply and internet connectivity, were most frequently cited. These responses reinforce the importance of addressing broader infrastructural deficiencies alongside technology-specific interventions.

Table 3. Adoption barrier rankings by mean severity score (n = 50; scale: 1 = Not a barrier, 5 = Major barrier)

Rank	Barrier	Category	Mean	SD	Severity
1	High Upfront Installation Cost	Economic	4.42	0.50	Critical
2	No Government Incentives	Economic	4.38	0.53	Critical
3	Lack of Policy Support	Institutional	4.38	0.49	Critical
4	Power Grid Instability	Technical	4.34	0.72	Critical
5	Lack of Protocol Standards	Technical	4.30	0.54	Critical
6	ROI Uncertainty	Economic	4.26	0.60	Critical
7	Absence of Building Energy Standards	Institutional	4.24	0.62	Critical
8	Weak Code Enforcement	Institutional	4.20	0.64	High
9	Interoperability with Legacy Systems	Technical	4.12	0.52	High
10	Limited Access to Finance	Economic	4.12	0.63	High
11	High Software Licensing Cost	Economic	4.12	0.48	High
12	Low Awareness Among Owners	Institutional	4.08	0.67	High
13	Poor Internet Connectivity	Technical	4.02	0.62	High
14	Skills Shortage	Institutional	4.00	0.64	High
15	Cybersecurity Risks	Technical	3.78	0.62	Moderate-High
16	Sensor Data Quality	Technical	3.54	0.61	Moderate-High

Lifecycle Cost Perceptions and Future Outlook

LCC importance was rated 4.64/5 (SD = 0.48), the highest mean score in the entire study, confirming that financial motivation for lifecycle cost management is strong and near-universal among respondents. The perceived potential of ML to reduce total lifecycle costs was rated 4.20/5 (SD = 0.64). The likelihood of IoT-ML investment within three years was rated 3.58/5 (SD = 1.11), moderate and contingent on demonstrated ROI. The most frequently requested support forms were training and capacity building (26%), pilot programmes (20%), case studies from Nigerian buildings (18%), and government grants (16%).

Reliability and Inferential Analysis

Internal consistency was assessed following George and Mallery's (2019) interpretive framework. The ML/AI scale returned $\alpha = 0.907$ (Excellent); Institutional Barriers $\alpha = 0.914$ (Excellent); Economic Barriers $\alpha = 0.806$ (Good); Technical Barriers $\alpha = 0.747$ (Acceptable); Lifecycle Cost Outlook $\alpha = 0.728$ (Acceptable); IoT Awareness $\alpha = 0.522$ (Below threshold heterogeneous items); Maintenance Practices $\alpha = -0.782$ (Inverse correlation distinct constructs, reflecting genuine conceptual independence rather than measurement error).

Table 4. Cronbach's alpha reliability analysis by scale (n = 50)

Scale	Section	Items (k)	Cronbach's α	Interpretation (George & Mallery, 2019)
ML/AI Familiarity & Adoption	D	4	0.907	Excellent
Institutional Barriers	E3	5	0.914	Excellent
Economic Barriers	E2	5	0.806	Good
Technical Barriers	E1	6	0.747	Acceptable
Lifecycle Cost Outlook	F	3	0.728	Acceptable
IoT Awareness & Adoption	C	4	0.522	Below threshold — heterogeneous items
Maintenance Practices	B	3	−0.782	Distinct constructs — negative covariance

Kruskal-Wallis H tests revealed that role type significantly differentiated IoT familiarity ($H = 12.786$, $df = 3$, $p = 0.005$) and ML familiarity ($H = 12.664$, $df = 3$, $p = 0.005$). BMS status produced the largest group effects: IoT familiarity ($H = 35.201$, $p < 0.001$) and ML familiarity ($H = 31.168$, $p < 0.001$). City significantly differentiated power outage impact ratings ($H = 8.331$, $p = 0.004$), with Lagos respondents rating both higher than Abuja. Spearman correlations identified IoT-ML familiarity co-development ($\rho \approx 0.65$, $p < 0.001$), direct power disruption experience and barrier severity ($\rho \approx 0.60$, $p < 0.001$), and LCC importance and ML reduction potential ($\rho \approx 0.45$, $p < 0.01$) as the most theoretically significant associations.

Discussion of findings

The finding that 58% of respondents rely on reactive or schedule-based maintenance with only 10% practising predictive maintenance directly corroborates the established characterisation of Nigerian facility management as dominated by a fix-on-fail paradigm (Ebiloma et al., 2023; NIESV, 2025). This pattern extends a well-documented trend in sub-Saharan African facility management that Atkin and Brooks (2021) describe as symptomatic of a sector that has not yet transitioned to condition-based or data-driven maintenance models. The mean financial impact of failures (4.0/5) and the high proportion of buildings spending more than 30% of OPEX on maintenance together confirm Ogunbayo et al.'s (2022) finding that maintenance budgeting and standardised management structures are absent across a significant portion of Nigeria's built environment, resulting in disproportionately inflated operational costs relative to developed-economy benchmarks documented by Flanagan and Jewell (2021).

The low-cost estimation accuracy means (3.36/5), and the 30% of buildings with no structured sensor data storage indicate that the analytical preconditions for predictive maintenance historical condition data, timestamped maintenance logs, and baseline performance records are absent. This resonates powerfully with Popovychenko et al.'s (2023) identification of the "problem of reliable data" as a central obstacle to WLA implementation in developing economies. Ebiloma et al. (2023) independently confirm this finding in the Nigerian context: the absence of systematic maintenance documentation is the primary barrier to the adoption of Industry 4.0 tools including sensors, machine learning, BIM, cloud computing, and IoT, precisely the tools this study finds underutilised in commercial high-rises.

The cost management methodologies advocated by Popovychenko et al. (2023) Target Costing, Kaizen Costing, and Standard Costing all demand baseline performance data and standardised cost records, and are therefore non-operational in Nigerian commercial high-rises until foundational data infrastructure is established. The BIM-LCCA integration framework proposed by Valinejadshoubi et al. (2024), combined with Jafary et al.'s (2025) BIM-CMMS framework within a Common Data Environment, provides a practically viable pathway for this data-building phase.

One of the most important findings of this study is the emergence of a willingness-capability gap within the Nigerian commercial real estate sector. Respondents demonstrated strong interest in adopting IoT and machine learning technologies when clear financial benefits could be demonstrated, yet simultaneously reported low levels of technical familiarity and limited access to skilled personnel. This suggests that the principal challenge is not resistance to innovation but the absence of the knowledge, skills, and institutional support required to implement it effectively. The finding shifts attention from technology acceptance toward capacity development as a critical enabler of digital transformation. This gap is structurally different from general technology resistance defined by Ancillai, Sabatini, Gatti and Perna (2023) as an attitudinal barrier within business model innovation contexts because, in the Nigerian context, the barrier is primarily evidentiary: respondents want to adopt but need locally grounded, empirically validated ROI evidence before committing capital.

This interpretation is consistent with Oladokun and Shiyanbola's (2021) finding that demand for sustainable building features in Lagos is driven overwhelmingly by cost saving (mean 3.79/4.0), with occupiers willing to pay premium rental for features that demonstrably reduce energy and operational costs. Bouabdallaoui et al. (2021) demonstrate that the technical pathway from data collection to fault prediction is operationally feasible, but note that predictive maintenance requires a higher initial investment in building automation systems relative to a reactive approach and that the complexity of autonomous fault determination represents a significant adoption barrier, precisely the barriers this study quantifies empirically (upfront cost 4.42/5; skills adequacy 2.98/5).

Scaife's (2024) systematic review of AI in facility operations maintenance establishes that artificial intelligence provides unbiased investment and repair recommendations from analysed data, and critically identifies insufficient data as the primary barrier to full AI implementation within a facility operations programme, independently confirming this study's finding that 30% of buildings maintain no structured sensor data storage. The 24% of respondents actively considering IoT-ML adoption represents the awareness-to-action transition stage that would benefit most from targeted demonstration programmes, identified by 20% of all respondents as their preferred support modality.

The power outage impact score (4.34/5) is the highest-rated single item in Section C and the fourth-highest rated barrier in the entire study. The strong Spearman correlation between direct power disruption experience and power grid instability as an adoption barrier ($\rho \approx 0.60$, $p < 0.001$) confirms the Diesel-Grid Paradox: the very infrastructure instability that makes IoT-ML systems most financially valuable also constitutes one of the primary barriers to their deployment (Orumwense et al., 2021; Karnilius et al., 2024).

Orumwense et al. (2021) provide crucial technical context: Nigeria's current electricity distribution system is unidirectional, employing electromechanical meters that cannot enable two-way data communication, the precise bidirectional architecture that IoT building management systems require. Their comparative analysis demonstrates that smart grid adoption would reduce transmission and distribution losses from over 10% to approximately 2%, enable self-healing characteristics preventing cascading outages, and replace blind monitoring with self-monitoring intelligence. The 4.1 billion IoT-connected commercial building devices projected globally by 2030 (Memoori Research Group, 2024) underscores the transformative potential that remains unrealised in Nigeria's commercial sector until national grid modernisation proceeds in parallel with building-level IoT deployment. Aboelmagd (2024), in a systematic review of IoT in smart building energy management, documents that substantial initial expenditures (averaging 15% of project budgets), data security issues, and system integration complexity are the principal barriers to IoT adoption in buildings globally, a pattern that resonates directly with this study's barrier hierarchy.

The smart grid benefits documented by Karnilius et al. (2024)- 15% energy consumption reduction and 20% peak demand reduction from smart meters, ADMS improvements in grid reliability — together with edge computing architectures that process sensor data locally at the building gateway, represent the most technically appropriate pathway for the Nigerian high-rise context, consistent with Nižetić et al. (2020).

The barrier ranking diverges significantly from global IoT adoption literature. Nižetić et al. (2020) identify technical barriers interoperability, data quality, and cybersecurity as the primary adoption constraints in smart building contexts. In contrast, this study finds that the top three ranked barriers are economic and institutional: High Upfront Cost (4.42), No Government Incentives (4.38), and Lack of Policy Support (4.38). This inversion echoes the pattern documented by Ojo et al. (2018) in their investigation of ICT deployment barriers in Nigerian real estate practice. A decade later, in the more advanced domain of IoT-ML, this structural pattern has deepened rather than resolved.

Popovychenko et al. (2023) identify closely analogous barriers to LCC/WLA implementation in developing economies: shadow economy effects, corruption risks, deficient strategic management, and inadequate legal frameworks compound the technical and data challenges. Significantly, they note that in developing countries WLA is only routinely applied when required by international financing institutions such as the World Bank — a fiscal and governance constraint mirrored in this study's finding at the building level. The mean regulatory supportiveness score of 2.52/5, the lowest in the entire study, quantifies the gap between the BEEC's stated ambitions and its operational reality. Abasilim and Esisio (2025) document that fragmented policies, inadequate cybersecurity regulation, and slow legislative processes collectively hinder digital technology adoption across Nigerian organisations. A comparison with the European Commission's (2025) building energy directive, which mandates performance thresholds with financial penalties and has demonstrably accelerated IoT adoption across the EU, underscores the regulatory gap that Nigerian policymakers must address.

The Kruskal-Wallis results demonstrate that professional role type is a significant differentiator of IoT and ML awareness. IoT vendors and energy consultants score substantially higher on familiarity and confidence, while facility managers and property managers, forming 72% of the sample, show considerably lower awareness. This professional knowledge gradient is consistent with Ebiloma et al.'s (2023) finding that Nigerian maintenance personnel lack the IT maturity and Industry 4.0 tool familiarity needed to implement digital maintenance management systems. The implication is that awareness and capacity-building initiatives must target practitioner-level professionals rather than the technology supply side, a conclusion directly aligned with the 26% of respondents who identified training and capacity building as their most needed support.

The BMS status findings are the strongest group effects in the study (H values of 35.2 and 31.2 respectively, both $p < 0.001$). Buildings with fully or partially operational BMS record dramatically higher IoT and ML familiarity scores, confirming that existing digital infrastructure is a strong predictor of adoption readiness and creating a self-reinforcing digital divide. This digital infrastructure precondition echoes Emedo et al.'s (2025) finding that buildings most likely to benefit from AI/ML value creation are precisely those that have already made prior investments in data collection infrastructure — a compounding advantage that policy interventions must specifically address for legacy building stock.

The LCC importance score of 4.64/5, the highest mean in the study, establishes that financial motivation for lifecycle cost management is near-universal among respondents. In the Nigerian context, extreme OPEX volatility driven by diesel price spikes, Naira depreciation on imported spare parts, and catastrophic system failures has created financial urgency sufficient to generate high LCC awareness even in the absence of sophisticated management tools. Orumwense et al.'s (2021) documentation that Nigeria loses US$985 million annually to power outages provides the macroeconomic scale to this micro-level finding.

The primacy of cost saving as a driver in this study (LCC importance 4.64/5) directly corroborates Oladokun and Shiyanbola's (2021) finding that cost saving was the highest-rated factor driving demand for sustainable attributes in Nigerian office buildings (mean 3.79/4.0). Together, the two studies establish a coherent picture: Nigerian commercial real estate practitioners understand the financial logic of energy efficiency and are willing to pay for features that deliver measurable savings; the necessary condition for IoT-ML investment exists in latent form, awaiting demonstration-based evidence to activate it.

Emedo et al. (2025) document that AI-driven systems achieve 17.6% operational cost reductions, 13.2% maintenance savings, and 14% energy savings performance improvements that could generate compelling ROI arguments for Nigerian commercial high-rise operators. However, these figures derive from developed-economy contexts. The BIM-LCCA integration framework proposed by Valinejadshoubi et al. (2024), combined with the Target Costing and Kaizen Costing methodologies advocated by Popovychenko et al. (2023), provides a methodologically coherent pathway toward generating the locally validated evidence base that this study's practitioners require.

Practical Implications

For facility managers and building owners, the study recommends prioritising the establishment of foundational data infrastructure, energy sub-metering, basic BMS, and structured maintenance logging as a prerequisite for IoT-ML deployment, rather than attempting to implement advanced ML without a data baseline. The BIM-LCCA integration approach of Valinejadshoubi et al. (2024), combined with Jafary et al.'s (2025) BIM-CMMS framework and the Target Costing and Kaizen Costing disciplines of Popovychenko et al. (2023), provides a practically implementable data-building framework. The finding from Oladokun and Shiyanbola (2021) that Lagos office occupiers already pay premium rent for energy-saving features provides a direct commercial incentive for owners to invest in IoT sub-metering and intelligent controls that enable demonstrable energy cost savings.

For policymakers, the regulatory supportiveness score (2.52/5) constitutes a clear mandate: BEEC enforcement must be strengthened with financial penalties and measurable compliance milestones, and fiscal incentives, such as import duty relief on IoT sensor hardware, tax credits for smart building investment, must be introduced to address the upfront cost barrier (4.42/5). The smart grid modernisation roadmap proposed by Orumwense et al. (2021), including Advanced Metering Infrastructure (AMI), substation automation, and Distributed Energy Resource (DER) incorporation, would fundamentally transform the energy infrastructure context within which IoT building systems operate, directly reducing the severity of the Diesel-Grid Paradox. Oladokun and Shiyanbola's (2021) recommendation that government subsidises locally made sustainable building features provides a complementary demand-side policy lever.

For technology vendors, free or subsidised pilot programmes are the most effective market-entry strategy identified by 20% of respondents as their most needed support modality. Vendors should prioritise edge computing architectures capable of operating under intermittent grid and internet conditions, as documented by Aboelmagd (2024). For researchers, multi-site longitudinal case studies documenting actual ML-driven maintenance cost reductions in Nigerian commercial high-rises, particularly those employing the Bouabdallaoui et al. (2021) five-step predictive maintenance framework adapted for grid-unstable environments, would provide the locally grounded evidence that practitioners need to convert high investment willingness (4.20/5) into committed capital allocation.

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4. CONCLUSION

This study investigated the adoption, barriers, and lifecycle cost implications of Internet of Things (IoT) sensor networks and machine learning technologies within commercial high-rise buildings in Lagos and Abuja, Nigeria. Through a survey of facility managers, property managers, building owners, developers, and technology practitioners, the research provides empirical insights into the current state of digital transformation within Nigeria's commercial real estate sector, drawing on a purposive sample of 50 practitioners across Lagos and Abuja (Patton, 2002). The study makes four principal contributions to the literature.

A key contribution of the study is the identification of a significant willingness-capability gap. Although stakeholders expressed strong interest in investing in digital technologies when presented with evidence of financial benefits, levels of machine learning familiarity and technical readiness remain relatively low. This suggests that future adoption efforts should focus not only on technology deployment but also on capacity development, skills acquisition, and knowledge transfer. This evidentiary character of the gap is reinforced by Oladokun and Shiyanbola's (2021) parallel finding that Nigerian commercial real estate occupiers demonstrate willingness to pay for energy-saving features when their value is tangibly demonstrated, and by Abasilim and Esisio's (2025) documentation of digital literacy deficits across Nigerian institutional contexts.

The study further demonstrates that economic and institutional barriers were perceived as more significant than technical barriers, contrasting with findings from smart-building studies in developed economies where interoperability and cybersecurity concerns are often dominant (Nižetić et al., 2020; Aboelmagd, 2024).

The barrier hierarchy challenges the global literature's prioritisation of technical constraints by demonstrating that economic barriers, particularly high upfront cost (4.42/5) and absence of government incentives (4.38/5), and institutional barriers, particularly lack of policy support (4.38/5) and weak enforcement (4.20/5), are rated more severe than any technical factor. Orumwense et al.'s (2021) documentation of the absence of a government smart grid implementation framework, and Popovychenko et al.'s (2023) observation that WLA is only applied in developing countries when mandated by international financing bodies, corroborate this hierarchy and demand that intervention strategies prioritise fiscal reform and regulatory strengthening over purely technical solutions. High installation costs, limited government incentives, and weak policy support were perceived as more severe obstacles than technical challenges. These findings indicate that successful implementation of IoT and machine learning technologies requires a supportive ecosystem encompassing financial incentives, regulatory frameworks, infrastructure improvements, and professional capacity building.

Another important finding is the central role of energy infrastructure in shaping adoption outcomes. The study identifies power supply instability as both a major operational challenge and a significant barrier to smart-building deployment, highlighting the interconnected nature of digital transformation and infrastructure development within emerging economies, it empirically validates the structural persistence of the fix-on-fail maintenance paradigm: 58% of buildings rely on reactive or schedule-based strategies, mean maintenance satisfaction is below the scale midpoint, and 30% of buildings maintain no structured sensor data infrastructure (Ebiloma et al., 2023; NIESV, 2025; Ogunbayo et al., 2022). This finding extends the ICT deployment barrier pattern originally identified by Ojo et al. (2018) into the IoT-ML domain, while connecting to Popovychenko et al.'s (2023) identification of data standardisation deficits as a fundamental obstacle to LCC/WLA implementation in developing economies.

Overall, the research confirms that IoT sensor networks and machine learning technologies possess considerable potential to improve lifecycle cost performance, enhance operational efficiency, reduce maintenance expenditure, and support sustainable building management in Nigeria. However, realising these benefits will require a gradual and context-sensitive transition from conventional maintenance models to data-driven asset management systems, suggesting a self-reinforcing digital divide consistent with Emedo et al.'s (2025) finding that AI value creation is highest in buildings that have already invested in data collection infrastructure.

5. COMPETING INTEREST

None to declare

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