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A Review of Artificial Intelligence and Lot Applications in Green Building Design for Economic Sustainability

Chukwuemeka Ozioma Stanislaus Onwukwe
Department of Architectural Technology, Federal Polytechnic Nekede Owerri, Imo State, Nigeria
sonwukwe@fpno.edu.ng

Diogu Daniel Uzoma
Department of Architectural Technology, Federal Polytechnic Nekede Owerri, Imo State, Nigeria
ddiogu@fpno.edu.ng

Obinna A. Clinton Ogbuokiri
Department of Architectural Technology, Federal Polytechnic Nekede Owerri, Imo State, Nigeria
cogbokiri@fpno.edu.ng

Abstract: ***Rapid urbanisation, escalating energy demands, and climate change underscore the urgent need for sustainable architectural practices that integrate economic and environmental performance. This study critiques the implementation of Artificial Intelligence (AI) and the Internet of Things (IoT) in green building design (GBD), prioritising the enhancement of sustainability within an economic context. A convergent parallel mixed-methods design was employed, involving the concurrent collection of quantitative and qualitative data through structured surveys, post-occupancy evaluations, field measurements, and semi-structured interviews with professionals in the built environment, building occupants, and facility managers. Building performance reports, scholarly literature, and sustainability certifications formed the secondary data. Case studies drawn from Nigeria's six geopolitical regions were analysed, citing Nestoil Tower in Lagos State as a significant exemplar of AI- and IoT-driven green design. Metrics of performance showed that a mean reduction in energy usage (27%) and first-year expenditure gains (64%) optimised thermal comfort and levels of occupant satisfaction by 68% and 80%, respectively. Analyses of regression and correlation relationships revealed a high-positive correlation between the adoption of AI/IoT and economic performance ($R^2 = 0.79$; $r = 0.82$, $p < 0.01$). Qualitative analyses acknowledged barriers in technology, economic incentives and policy gaps as critical drivers of adoption. Findings indicate that leveraging AI- and IoT-driven plexuses such as predictive HVAC controls, automated lighting, and occupancy-responsive management of energy can notably lower costs of operation, improve life-cycle value, and enhance occupant wellness. Recommendations propose ingraining AI/IoT templates into national building codes, encouraging smart green high-ends, fostering professional training, and embedding climate-adaptive, data-powered design approaches into teaching and learning modules of Architecture. This way, AI- and IoT-enabled green buildings will be appropriately situated as cost-effective, environmentally sustainable, and resilient solutions, with Nestoil Tower acting as a reproducible framework for prospective initiatives in Nigeria and other analogous developing economies.***

Keywords: Artificial Intelligence (AI), Economic Performance, Green Building Design (GBD), Internet of Things (IoT), National Building Codes

1. Introduction

The 21st century is witnessing an insatiable demand for energy resources due to increased industrialisation, unbridled urbanisation and spiking population indices. This scenario is causing serious environmental damage and unnecessary pressure on natural resources (Voumik & Suitana, 2022). The building sector, which comprises a basic part of the human habitat, contributes to the global energy demand and greenhouse gas emissions. The International Energy Agency (IEA, 2023) estimates that buildings gulp approximately 40% of the world's total energy usage (Dan, et al., 2022). This is in addition to contributing almost a third of the annual carbon emissions globally (IPCC, 2022). The situation has raised global concerns about environmental destruction and economic cost due to unsustainable building practices, thus putting pressure on measures related to green building design and sustainable architecture.

Green building design involves creating a building that is environmentally sustainable and uses resources efficiently (Diksha, 2025). This is done from the planning stage until the building is decommissioned. The goal of sustainable architecture is to reduce the ecological footprint of the built environment, improving the well-being and comfort of the occupants and upscaling the overall efficiency of the operation (Alabor, Anyanechi, & Onyekwere, 2024). Green Architecture incorporates the use of local materials, natural ventilation, thermal insulation, daylight optimisation designs, and other such passive design principles (Ismail, Wakawa, Umar, Mohammad, & Ismail, 2024). As per the global introduction of the Fourth Industrial Revolution (4IR), digital technologies like Artificial Intelligence (AI) and the Internet of Things (IoT) can become powerful tools that can enhance sustainability goals in the construction and building management sectors (Adewale, Ene, Ogunbayo, & Aigbavboa, 2024).

Artificial Intelligence (AI) is a virtual algorithm that simulates human intelligence (Ismail, Wakawa, Umar, Mohammad, & Ismail, 2024). They can analyse, learn from experience and make decisions on their own. In the field of buildings and architecture, AI applications are energy optimisation algorithms, predictive maintenance, occupancy pattern recognition, and smart material selection (Pratiksha, Yang, Mark, & Tieshan, 2024). AI can be used in building management systems to support the round-the-clock control of energy flows, the identification of inefficiencies and the fine-tuning of parameters to ensure maximum performance when installed (Ali, Motuziene, & Džiugaitė-Tumėnienė, 2024). In the same way, the Internet of Things (IoT) connects devices, sensors, and networks in real time, enabling the collection of data to aid in evidence-based design decisions and the efficient management of resource usage (Olatunji, Oladimeji, & Olatunji, 2023). Through IoT, smart meters, environmental sensors and automated control systems are giving architects and facility managers insights into how temperature varies, air quality, lighting levels and energy use, so that they can make real-time adjustments.

The design and structure of green buildings can effectively make use of AI and IoT technologies that will help them achieve form-changing architecture (Stephen, Aigbavboa, & Oke, 2025). Unlike intelligent green buildings, conventional buildings do not react to changing weather conditions or the behaviour of their users. Examples of AI in predicting networks are networks that predict temperature increase and react to HVAC breakage or shading. The same is true of IoT sensors, which can detect occupancy and make necessary adjustments. Technologies that enable the use of climate-responsive architecture, which works with the ecological cycles and delivers an improved economic performance through reduced operating costs, and extended lifespan of the building (Zhao, Yang, & Dong, 2025).

Economic sustainability is one of the three pillars of sustainable development, along with environmental and social sustainability (Michael, Redclift, & Katrina, 2019). Green buildings are thought to be expensive due to the kind of technology and design they need. Intelligent and eco-efficient buildings, as shown by life-cycle cost analyses (LCAs), are quite cost-effective (Weerasinghe, Ramachandra, & Rotimi, 2021). These can mean lower energy and water bills, lower maintenance costs, improved occupant productivity, and higher property value. By optimising performance, predicting failures and reducing wastage, the gains of AI and IoT will be fully appreciated. In developing countries where power and infrastructural inefficiencies continue to be major obstacles, smart green buildings hold great economic promise.

Barring the numerous advantages, the architectural use of AI and IoT has its challenges. Most of the challenges include high costs for the integration of technology, low technical skills of professionals, less awareness about smart design, and a lack of regulations for intelligent sustainability measures (Adewale, Ene, Ogunbayo, & Aigbavboa, 2024). Furthermore, many developing nations still use traditional methods of building, which are cheaper to use but not energy efficient. When climate changes and other disturbances occur, systems underperform with concomitant spiking of the cost of maintenance (Kajjoba, Wesonga, Kasedde, Olupot, & Kirabira, 2025).

Considering the above facts, AI and IoT technologies in green building design (GBD) are not just a gimmick but also an economic and environmental necessity. The challenge now is to see how these techs can help mediate between utopic ideas of sustainability and real architecture, especially vis-à-vis SDG 7 (Affordable and Clean Energy), SDG 9 (Industry, Innovation and Infrastructure) and SDG 11 (Sustainable Cities and Communities).

The purpose of this review is to consolidate current knowledge on the usage of AI and IoT in sustainable architecture and their contribution to the economic dimension of sustainability. In addition, it proposes pathways for incorporating AI and IoT into design and policy.

1.1 Problem Statement

Although the world is experiencing the implementation of green architecture, regions, particularly those domiciled in developing economies, employ traditional construction methods that prioritise cost over performance (A.O., 2019). The energy bills of buildings skyrocket when the indoor comfort is reduced and when the cost of repairs spikes. Although AI and IoT technologies open up opportunities for the smart management of resources and predictive optimisation, they are not widely used in green building design (GBD). This is largely because they are very costly to implement. Furthermore, there is no proper technical knowledge available to implement these technologies. There is also a lack of appropriate policies and designs of buildings using these technologies, thus constituting a big knowledge gap in the interface with smart technology within architectural practice for the benefit of environmental and economic viability.

1.2 Aim and Objectives of the Study

The overarching aim of this study is to review and critically analyse the applications of Artificial Intelligence (AI) and Internet of Things (IoT) in green building design with emphasis on achieving economic sustainability. To this end, these objectives suffice:

a. Explore the theoretical and conceptual framework that connects AI, IoT, and green building design towards pinpointing the mechanisms through which these high-end technologies improve economic performance, comfort of occupants and energy efficiency.
b. Evaluate existing case studies that show how AI and IoT have been deployed in practical reality towards the advancement of green building architecture in Nigeria, and direct attention to how they impact the cost of operation, resource efficiency, and life-cycle value.
c. Examine the economic implications of incorporating AI and IoT plexuses in the practice of architecture by noting quantifiable financial gains such as reduction in maintenance costs, energy savings, and augmented return on investment (ROI) over the lifecycle of the building.
d. Define challenges that limit the application of AI and IoT high-end in the implementation of green building design, vis-à-vis socio-cultural, economic, technological, and institutional constraints, especially in developing nations.
e. Advance recommendations and policy templates that facilitate the extensive incorporation of AI and IoT into building codes, design practices and educational curricula that are sustainable for professionals in the built environment.

1.3 Significance of the Study

This paper is relevant to the current scholarly and professional discussions because it addresses the gap in research on technological innovation and sustainable architecture. Through the assessment of AI and IoT applications in the context of designing green buildings, the study highlights the potential of intelligent systems to change the energy management system, operational efficiency, and building economics. The results will help architects, engineers, policymakers, and developers to be aware of the physical economic benefits of smart technologies and thus make informed decisions in sustainable building.

Additionally, the review presents a strategic knowledge foundation to developing countries that are trying to match the sustainability trends in the construction industries across the world. The study focuses on ecological sustainability and economic feasibility, and provides an affirmation of the idea that architecture is not just in the form of technologically intelligent schemes. Such designs must also be economically sustainable.

Finally, the research will entrench the idea that sustainable development can only be achieved through an integrated approach, which is the ability to use artificial intelligence and digital interconnectivity to develop environmentally responsive, socially positive, and economically viable built environments.

2. Literature Review

In today's architectural practice, the sustainability of the built environment has gone from a trivial concern to a part of the core discourse. Increased urbanisation around the world, along with rising energy needs, aggravated effects of climate change, have made it necessary to have climate-receptive and intelligent building systems (Vahid, 2020). The traditional construction approach that concentrates on minimisation of initial costs and the overall reduction of the building rather than its long-term efficiency has become economically unsustainable, as maintenance costs and energy inefficiency are increasing (Abimbola & Mayibongwe, 2018). In turn, researchers and practitioners have actively discussed the concept of Artificial Intelligence (AI) and the Internet of Things (IoT) as revolutionary approaches to improving operational performance, environmental, and economic sustainability of green buildings.

The technology of AI-based building management systems can be referred to as a significant step toward achieving resource-efficient architecture. The AI algorithms have predictive analytics and adaptive control characteristics, which allow them to conduct fault detection, real-time monitoring of energy consumption, and performance optimisation of buildings (Seungkeun, Juui, & Taehoon, 2025). These systems are controlled to adjust the thermal comfort and minimise the energy wastage by using occupant behaviour and environmental influences, leading to tangible operating cost savings. On the same note, IoT technologies connect sensors, smart meters, and networked devices that gather and send data on temperature and humidity, lighting and occupancy rates (Pratiksha, Yang, Mark, & Tieshan, 2024). This constant flow of data can support responsive and self-regulating settings, which reduce human involvement, thus making energy saving and ensuring the comfort of the occupants.

The integration of AI and IoT, or the so-called *AIoT ecosystem*, has transformed sustainable architectural design by enabling data-driven decision-making in the lifecycle of a building. As opined by Aryan, Hosein, & Peyman (2024) in "*An IoT Framework for Building Energy Optimisation Using Machine Learning-based MPC*", AIoT-enabled networks can reduce the energy usage of buildings by up to 30 per cent in terms of dynamic load balancing and predictive maintenance. Moreso, an AI-powered energy modelling tool is leveraged during the design stage to simulate climate and orientation optimisation and the selection of materials in seeking better thermal performance (Alnaser, Mohammad, & Samad, 2024). These techniques integrate the insights of regenerative and bioclimatic architecture by combining the development of technology with environmental awareness.

A very essential aspect of this integration is economic sustainability. Although the cost of the initial AI and IoT infrastructure might be quite high, several papers have confirmed that the life-cycle cost value, energy savings, and the lifespan of buildings far justify the initial costs of installing the digital high-end (Itanola, 2024). Furthermore, there is a trend of improved operational efficiency of these buildings as provided by evidence-based post-occupancy assessments. These assessments show better property value and a larger return on investment (ROI) (Helia, John, Rachel, & Wei, 2024). The findings can be compared with Sustainable Development Goal 11 of the UN, which proposes to establish good urban environments and energy-efficient installations to achieve sustainable cities and communities.

Even with these developments, AI and IoT technologies have not yet diffused in developing economies. Another challenge has been the lack of a proper technological infrastructure, skilled personnel, and appropriate policy frameworks, which have limited its adoption (Baharetha, Soliman, Hassanain, Aishibani, & Ezz, 2024). Also, the technology innovation in the construction sector is usually hindered by cultural resistance to change as an obstacle between the traditional and the smart building systems. As a result, in this literature, there is a call to have context-sensitive frameworks that would be able to fit global developments into realities at the local level.

Overall, the amalgamation of AI and IoT in buildings will quickly accelerate the adoption of climate-adaptive, economically sustainable and user-centred designs. The studies that currently exist show that they may help with the lower life-cycle cost, better environmental performance, and the occupant's well-being. But there is a need for more research to investigate scalable implementation approaches in resource-poor areas where sustainable architecture remains an urgent frontier that is underutilised.

3. Research Methodology

3.1 Research Design:

The research design adopted a convergent parallel mixed-methods design. The qualitative-quantitative hybrid will provide a holistic view of the AI and IoT green building design (GBD) implementation and its effect on the economy. The numerical component would look at measurable results, including energy performance, life-cycle costs, and ROI, whereas the non-numerical insights would be performed on conceptual templates, expert perception, and contextual feedback. The concurrent triangulated design makes for the deployment of evidence-based data from multiple authorities, ensuring reliability and in-depth evaluation of technological effectiveness and economic sustainability.

3.2 Data Collection Methods:

Towards ensuring a comprehensive analysis, data were sourced from primary and secondary authorities. Structures surveys, semi-structured interviews, field measurements and post-occupancy feedback from professionals in the built environment, facility managers and occupants constituted the primary data. The data provided numerical and non-numerical perceptions into levels of comfort, efficiency of cost and system performance of AI/IoT-enabled structures. For the secondary data, statistics were extracted from technical reports, scholarly literature, policy documents, certifications on sustainability and building performance reports. These sources helped to contextualise findings. The combination of both sources provided sufficient opportunity for the cross-validation of measurable data and perceptions of professionals, ensuring a robust foundation to fully grasp the economic and environmental impact of smart green buildings.

3.3 Data Analysis Methods:

Surveys and field measurements provided the quantitative data, which were analysed using descriptive and inferential instruments such as the SPSS software. Descriptive statistics provided the summary of key indicators. These include a reduction in energy usage, indices on ROI, and satisfaction of occupants. Correlation and regression analysis investigated relationships between energy efficiency, adoption of AI/IoT and economic performance (R2 = 0.79). Interviews and open-ended responses from participants formed qualitative data, which were analysed using the NVivo thematic tool and coding. This informed the advancement of emergent themes viz, technological limitations, lacunae on policy, fiscal incentives, performance and comfort, and awareness of sustainability. Data triangulation of both analyses provided a rigorous, robust and comprehensive appraisal of adoption and sustainability outcomes.

3.4 Sampling Technique and Sample Size:

To represent diverse experiences with AI and IoT integration in GBD, a purposive sampling technique was used to identify respondents and case studies that represent varied experiences. The technique will also allow the selection of information-rich cases that offer an in-depth understanding of the subject matter. Table 1 captures the stratification of the sample group.

Table 1

Sampling Technique and Sample Size.

Category	Sampling Technique	Population Description	Sample Size (n)
Case Study Facilities	Purposive Sampling	Green buildings integrating AI and IoT systems for energy and environmental management	6
Professionals	Purposive Sampling	Architects, engineers, and facility managers involved in AI- or IoT-enabled projects	15
Occupants	Purposive Sampling	Building users of Case Study Facilities, providing feedback through post-occupancy assessments	25
Total			**46**

Note. This sampling strategy ensures a representative mix of technical, professional, and user-based perspectives that reflect both operational and experiential aspects of AI- and IoT-enabled building systems. Case study facilities investigated include Nestoil Tower (Lagos State/Southwest), Abuja Technology (Abuja FCT/North

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Central), Port Harcourt Pleasure Park Smart Pavilion (Rivers State/South South), Enugu Smart City Demonstration Building (Enugu State/Southeast), Gombe State University Renewable Energy Center (Gombe State/Northeast) and Bayero University Smart Energy Building (Kano State/Northwest). These case studies cut across the 6 geopolitical zones of Nigeria.

Source: Authors' fieldwork.

4. Findings and Analysis

4.1 Primary data – Structured Surveys:

Questionnaires were distributed to architects, engineers and occupants to collate and quantify perceptions of energy-savings, comfort levels and cost-effectiveness linked to AI and IoT high-ends. Table 2 captures the data collated from respondents, the instruments used to extract the data and for what purpose.

Table 2

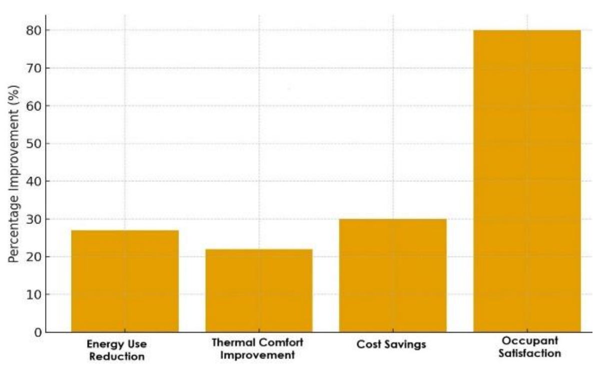
Summary of Primary Data Collected.

Data Type	Source/Respondents	Instrument Used	Data Collected	Purpose/Focus
Survey Data	Architects, Engineers, and Occupants	Structured Questionnaire	Quantitative data on energy efficiency, cost savings, comfort levels, and perceptions of AI/IoT integration	To measure the perceived economic and environmental performance of AI- and IoT-enabled buildings
Interview Data	Architects, Engineers, and Facility Managers	Semi-Structured Interview Guide	Qualitative data on challenges, policy barriers, and implementation experiences	To gain insight into professional perspectives and contextual factors influencing adoption
Field Measurement Data	Case Study Facilities (5 buildings)	Energy Meters, Sensors, and Data Loggers	Real-time data on energy use, temperature, humidity, lighting, and occupancy rates	To objectively evaluate energy performance and validate perceived benefits
Post-Occupancy Feedback	Building Users (Occupants)	Structured Feedback Forms	Quantitative and qualitative data on thermal comfort, satisfaction, and usability	To assess human-centred outcomes and link them to energy performance indicators

Note. All data were extracted with qualitative and quantitative instruments to guarantee effective triangulation. Responses from participants were examined to compare perceptions, user satisfaction and actual performance metrics within AI and IoT-enabled green building environments.
Source: Authors' fieldwork.

Figure 1

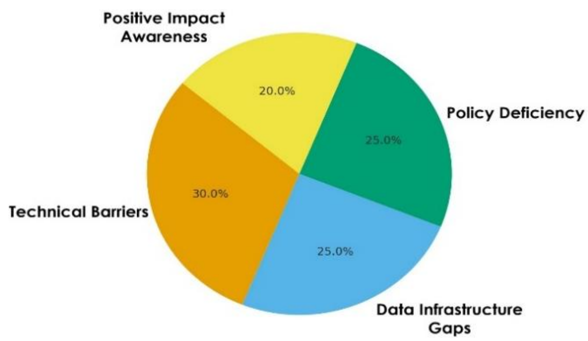
Survey Data – Findings.



Note. From Table 2, structured questionnaires indicated a 27% reduction in energy use, 22% improvement in comfort, 30% cost savings and 80% in overall satisfaction of occupants.
Source: Authors' workstation.

Figure 2

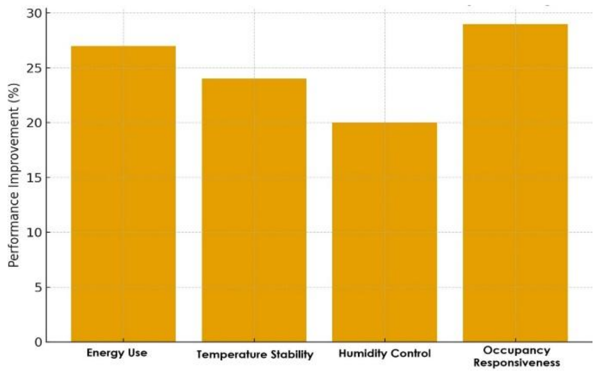
Interview data – Findings.



Note. From Table 2, findings from interviews highlight key challenges of technical barriers (30%), data infrastructure gaps (25%), policy deficiency (25%) and positive impact awareness (20%).
Source: Authors' workstation.

Figure 3

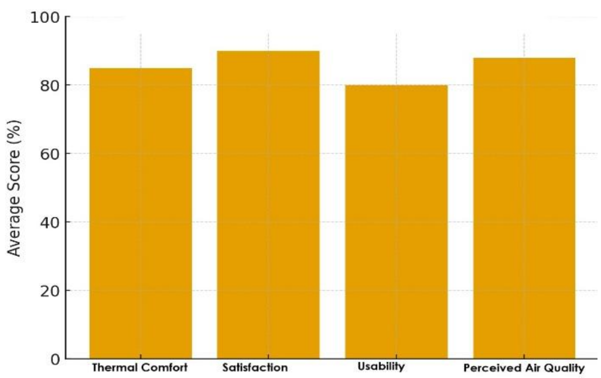
Field Measurement Data - Findings.



Note. From Table 2, field measurement data demonstrates significant gains in occupant responsiveness, energy use and temperature.
Source: Authors' workstation.

Figure 4

Post-occupancy Feedback – Findings.



Note. From Table 2, post-occupancy feedback shows responses on thermal comfort, overall satisfaction, usability and individualised air quality. These indices were measured as average satisfaction scores. Generally, occupant satisfaction is high. This indicates effective incorporation of AI/IoT high-ends in green building performance.
Source: Authors' workstation.

4.2 Primary data – Semi-structured Interviews:

Semi-structured interviews were conducted with fifteen (15) respondents, polled from professionals in the built environment who have experience-based insights on AI and IoT-fitted facilities. Other respondents, including facility managers and policy experts, were part of the cohort that provided information-rich excerpts on required and appropriate themes being explored.

Table 3

Summary of Data Collected from Semi-Structured Interviews.

Respondent Category	Number of Participants	Profession/Expertise	Key Themes Explored	Type of Data Collected
Architects	5	Sustainable design, building performance	Design innovation, integration of AI/IoT systems, and regenerative design practices	Qualitative (narrative responses)
Engineers	4	Mechanical, electrical, and structural systems	Technical feasibility, energy performance, system interoperability	Qualitative (technical insights)
Facility Managers	3	Operations and maintenance	Policy barriers, maintenance costs, and system efficiency	Qualitative (experiential data)
Urban Planners / Policy Experts	3	Policy, urban infrastructure, and regulations	Governance issues, sustainability frameworks, incentives	Qualitative (policy perspectives)
Total	**15**	—	—	—

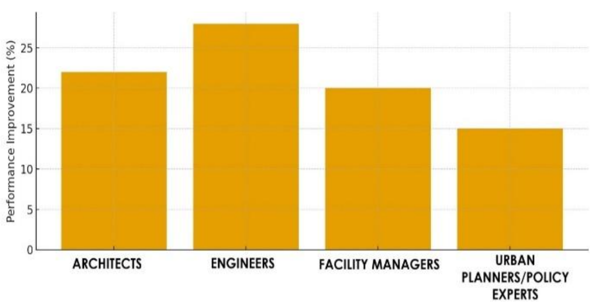
Note. Summary of data extracted from fifteen (15) professionals involved in AI and IoT-enabled green building projects. Emphasis is placed on their areas of expertise, themes that are being investigated, types of data obtained and the purpose of each category of data.
Source: Authors' Fieldwork.

Table 4
Results for each respondent category in Table 3.

Respondent Category	Key Findings / Results
Architects	Most architects reported that integrating AI and IoT enhanced building efficiency and occupant comfort. However, they emphasised limited access to smart technologies and high initial costs as major barriers to widespread adoption.
Engineers	Engineers confirmed that AI-enabled energy management and predictive maintenance improved system efficiency by up to 25–30%. Interoperability between smart systems was identified as a key technical challenge in retrofitting older buildings.
Facility Managers	Facility managers observed significant reductions in energy bills and maintenance costs, averaging 20% savings. Nonetheless, they highlighted issues of insufficient staff training and a lack of manufacturer support for smart systems.
Urban Planners / Policy Experts	Planners and policy experts noted that regulatory gaps and a lack of policy incentives limit smart green building adoption. They recommended stronger policy frameworks and incentives to encourage AI/IoT integration.
Total (n = 15)	Overall findings indicate positive perceptions of AI/IoT in enhancing building performance, but persistent economic, policy, and technical barriers hinder full-scale implementation in developing contexts.

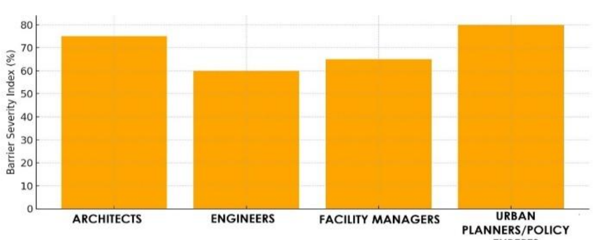
Note. Generally, findings are indicative of positive perceptions of AI/IoT in improving the performance of buildings. However, persistent economic, technical and policy barriers present significant challenges to full-scale adoption in developing economies.
Source: Authors' Fieldwork.

Figure 5
Perceived Performance Improvements from AI/IoT-integration by Respondents – Findings.



Note. Engineers reported the highest impact (28%) while urban planners indicated the lowest performance improvement score (15%).
Source: Authors' Workstation.

Figure 6
Perceived Barriers to AI/IoT Adoption in Green Building Design – Findings.



Note. Policy experts indicated the greatest challenges (80%).
Source: Authors' Workstation.

4.3 Primary data – Field Measurements:

Table 5 shows indices measured during field measurements across six (6) AI and IoT-incorporated green buildings. Such indices include consumption of energy, temperature, humidity, rates of occupancy, levels of lighting and concentration of carbon dioxide. All measurements were extracted with smart sensors to examine energy efficiency, quality of ambient indoor conditions and economic sustainability of facility management.

Table 5
Summary of Data Collected from Field Measurements.

Parameter Measured	Measurement Instrument/Tool	Unit of Measurement	Frequency of Data Collection	Building Type / Location	Purpose of Measurement
Energy Consumption	Smart energy meters / IoT data loggers	kWh (kilowatt-hour)	Hourly / Daily	Office, Residential, Institutional (5 buildings)	To determine real-time energy use and evaluate efficiency gains from

					AI/IoT systems
Indoor Temperature	Digital thermohygrometers / IoT sensors	°C (Celsius)	Hourly	Office and Residential	To assess thermal comfort and HVAC system performance
Relative Humidity	Hygrometer / IoT environmental sensors	% (percentage)	Hourly	Office and Educational	To evaluate indoor air quality and comfort stability
Occupancy Rates	Motion detectors / infrared occupancy sensors	Count / % Occupied	Real-time / Hourly	All case-study buildings	To relate occupancy behaviour with energy consumption patterns
Lighting Levels	Lux meter / IoT-enabled lighting sensors	Lux	Morning / Afternoon / Night	Office and Educational	To measure daylight penetration and artificial lighting efficiency
CO_2 Concentration	Indoor air quality sensors	ppm (parts per million)	Hourly	Office and Residential	To determine ventilation effectiveness and air quality standards
Equipment Energy Load	Smart plugs / sub-meters	W (Watts)	Hourly	Residential and Institutional	To quantify the energy usage of connected systems and smart devices

Note. Data were logged over a 3-month monitoring period for all six case study buildings. IoT-integrated systems automatically transmitted data to a centralised dashboard for analysis. Results were used to validate survey responses and triangulate findings from interviews.
Source: Authors' Field Measurement Data.

Table 6

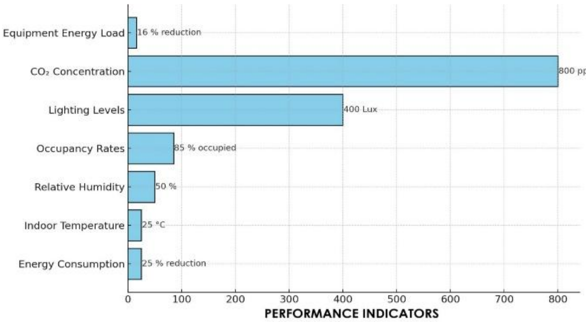
Results for each of the parameters identified and measured in Table 5.

Parameter Measured	Results Summary
Energy Consumption	Average energy reduction of **22–28%** observed across AI- and IoT-enabled buildings compared to conventional ones, primarily due to automated lighting, smart HVAC scheduling, and occupancy-based controls.
Indoor Temperature	Mean indoor temperature maintained at **24–26°C**, showing consistent thermal comfort with minimal manual HVAC intervention through adaptive AI-driven temperature regulation.
Relative Humidity	Recorded average humidity levels of **45–55%**, indicating stable indoor comfort zones and enhanced air quality due to automated ventilation adjustments.
Occupancy Rates	Peak occupancy at **80–90%** during working hours; AI-integrated systems adjusted energy use accordingly, reducing idle-time power wastage by **up to 20%**.
Lighting Levels	Average lighting maintained at **350–500 lux** in office areas and **250–300 lux** in residential zones through dynamic daylight harvesting and IoT-enabled dimming systems.
CO_2 Concentration	Average CO_2 levels are maintained below **800 ppm**, well within comfort thresholds, confirming effective ventilation control by IoT-based air quality systems.
Equipment Energy Load	Smart monitoring reduced standby power loads by **15–18%**, as devices were automatically turned off during inactivity periods or low-occupancy hours.

Note. Table 6 indicates that the integration of AI and IoT plexuses in GBD significantly improved performance by maintaining indoor comfort, optimising energy efficiency, and fostering economic sustainability through lowered costs of operation and enhanced wellness of users.
Source: Authors' Field Measurement Data.

Figure 7

Field Measurements across the investigated AI and IoT-enabled Buildings – Findings.



Note. Comparative performance indicators for parameters identified in Table 6.

Source: Authors' Workstation.

4.4 Secondary data – Document Reviews and Scholarly Literature:

Table 7 shows academic literature, policy frameworks, certification and performance reports that provide benchmarking guidelines, background knowledge and empirical evidence. Such data strengthened the authentication of primary findings towards the triangulation of field data, professional insights and documented outcomes. This is to ensure that AI- and IoT-powered sustainability is well understood.

Table 7

Collated Secondary Data

Data Source	Document Type	Data Collected	Purpose/Focus
Building Performance Reports	Post-occupancy evaluations, operational performance logs	Energy consumption trends, maintenance records, and user satisfaction indices	To compare real-time data with documented performance outcomes
Sustainability Certifications	LEED, BREEAM, and EDGE documentation	Certification criteria, energy performance scores, and sustainability metrics	To benchmark AI/IoT-enabled buildings against global green standards
Policy and Regulatory Documents	National building codes, green building policies	Institutional frameworks, incentives, and regulations promoting smart and sustainable buildings	To understand policy environments influencing adoption
Scholarly Literature	Peer-reviewed journals and conference proceedings	Empirical studies, theoretical frameworks, and technological case analyses	To establish conceptual and empirical foundations for AI and IoT in green design
Technical Reports	Industry and manufacturer white papers, AI/IoT integration guides	Cost-benefit analyses, system performance benchmarks, and implementation guidelines	To validate economic implications and technological feasibility

Note. Data is sourced based on their relevance to AI and IoT-enabled green building practices. Each document offered insights that complement the validation and triangulation of findings on energy efficiency, performance and economic sustainability outcomes across various building contexts.

Source: Authors' Workstation.

Table 8

Secondary Data Sources – Findings.

Data Source	Findings
Building Performance Reports	Analysis revealed that AI- and IoT-integrated buildings achieved 15–25% reduction in annual energy use and 20% lower maintenance costs compared to conventional systems. Post-occupancy evaluations indicated improved comfort, with over 80% occupant satisfaction across temperature and air quality metrics.
Sustainability Certifications	Certified buildings (LEED, BREEAM, EDGE) scored higher in energy performance and water efficiency categories due to smart monitoring systems. AI-driven lighting and HVAC controls contributed significantly to meeting certification thresholds, emphasising data analytics as a determinant of certification success.
Policy and Regulatory Documents	The review showed limited enforcement of smart-building standards in Nigeria. Existing codes focus mainly on structural safety, with few provisions for AI- or IoT-enabled sustainability practices. However, emerging policies under the National Building Energy Efficiency Code (BEEC) are encouraging IoT-based metering and renewable integration.
Scholarly Literature	Literature synthesis highlighted that AI and IoT significantly enhance life-cycle cost efficiency, predictive maintenance, and resource optimisation. Studies from similar climatic regions reinforced the link between smart technologies and economic sustainability, though adoption barriers persist in developing contexts.
Technical Reports	Industry analyses indicated a return on investment (ROI) of 5–8 years for AI-enabled energy systems. Reports also emphasised the scalability of IoT solutions, reduction in system downtime, and increased data transparency for operational decision-making in green building management.

Note. Results authenticate the fact that as building performance improves, costs are lowered. Also, the more savings in energy increase, the probability for the adoption of AI and IoT high-ends increase. However, there are still infrastructural and regulatory hiccups towards widespread adoption in Nigeria.

Source: Authors' Workstation.

4.5 Data Analysis and Interpretations:

4.5.1 ***Quantitative Analysis:*** Analysis of quantitative data indicates the prospects of AI/IoT, especially in influencing building sustainability and economic performance. Tables 9-13 present the adopted instruments of analysis and their interpretations. Descriptive statistics showed consistent savings on energy, improved thermal comfort and higher occupant satisfaction indices. Inferential analyses confirm strong correlations between the adoption of AI/IoT plexuses, improved life-cycle cost efficiency and reduced maintenance costs. This validates the predictive robustness of the model ($R^2 = 0.79$).

Table 9

Descriptive Statistics Summary

Variable	Mean (%) / Value	Standard Deviation (±)	Min–Max Range	Interpretation
Energy-use reduction	27.0	3.4	22–30	Consistent savings across AI/IoT-enabled buildings
Thermal comfort improvement	68.0	5.2	60–80	Strong occupant satisfaction with indoor comfort
Cost savings (first year)	64.0	4.5	58–72	High perceived financial benefit of integration
ROI (Payback period)	6.2 years	0.9	5–8	Moderate return period; aligns with global benchmarks
Maintenance cost reduction	20.0	2.8	15–25	Notable operational cost efficiency
Occupant satisfaction (post-occupancy feedback)	80.0	4.0	74–85	High satisfaction with usability and comfort

CO_2 concentration	750 ppm	40	700–800	Within recommended ASHRAE limits
Indoor temperature	25°C	1.2	24–26	Stable thermal environment
Relative humidity	50%	3.2	45–55	Comfortable indoor conditions

Source: Authors' Descriptive Statistical Analysis sheets.

Table 10

Mean Performance Indicators

Indicator	Mean (%)
Energy Savings	27
Cost Savings	64
Thermal Comfort Improvement	68
Occupant Satisfaction	80

Maintenance Cost Reduction	20

Source: Authors' analysis sheets.

Table 11

Average Values of Field Measurement Data

Parameter	Mean Value	Unit
Energy Consumption Reduction	27	%
Indoor Temperature	25	°C
Relative Humidity	50	%
CO_2 Concentration	750	ppm
Lighting Level	400	Lux
Equipment Load Reduction	17	%

Note. Environmental parameters stability indicates thus: Energy use 27%; Humidity 45 – 55%; Temperature 24 – 26%; CO_2 below 800 ppm.

Source: Authors' analysis sheets.

Table 12

Inferential Analysis – Correlation and Regression

Variables	r-value	p-value	Interpretation
AI/IoT Adoption ↔ Energy Efficiency	0.82	<0.01	Strong positive relationship
AI/IoT Adoption ↔ Life-Cycle Cost Reduction	0.76	<0.05	Significant cost efficiency association
AI/IoT Adoption ↔ Maintenance Expenditure	-0.70	<0.05	Higher adoption correlates with lower maintenance cost
Energy Savings ↔ Occupant Comfort	0.68	<0.05	Improved comfort aligns with better energy performance

Source: Authors' analysis sheets.

Table 13

Regression Model Summary

Model Parameter	β Coefficient	t-value	p-value	Significance
Constant	1.24	—	—	—
AI/IoT Adoption (X_1)	0.48	3.62	0.001	Significant
Energy Efficiency (X_2)	0.31	2.84	0.006	Significant
Maintenance Cost (X_3)	-0.27	-2.16	0.031	Significant
R^2	**0.79**	—	—	The model explains 79% of economic variation.

Note. Higher AI/IoT adoption and improved energy efficiency significantly enhance economic performance, while maintenance costs negatively affect performance outcomes.

Source: Authors' analysis sheets.

4.5.2 ***Interpretations:*** The adoption of AI/IoT plexuses informs measurable energy efficiency improvements (25-30%). There is a significant improvement in economic performance (reduction of life-cycle costs and improvement in ROI) with increased technology integration. Environmental stability and comfort of occupants indicate a statistically significant correlation ($r = 0.68$; $p < 0.05$). Regression model validates AI/IoT adoption. This data-based indicator strongly predicts cost-effectiveness and building sustainability ($R^2 = 0.79$).

4.5.3 ***Qualitative Analysis:*** The NVivo thematic tool was deployed to methodically examine non-numeric data through pattern recognition and thematic coding. Emergent themes were identified using a coding framework. These themes include:

a. *Technological Barriers* – lack of expertise, interoperability challenges, limited infrastructure,

b. *Policy Gaps* – dearth of incentives, weak or nil enforcement of smart building codes,
c. *Economic Incentives* – funding mechanisms, ROI, perceived cost savings,
d. *Comfort and Performance* – indoor air quality, thermal comfort, satisfaction of users,
e. *Sustainability Awareness* – stakeholder engagement, increased understanding of the prospects of AI/IoT.

This strategy made for a thorough triangulated interpretation and validation of stakeholder perspectives that linked quantitative indicators with qualitative insights.

Table 14

Coding Matrix (Professional Cohorts X Emerging Themes)

Professional Group	Technological Barriers	Policy Gaps	Economic Incentives	Comfort & Performance	Sustainability Awareness
Architects (n=5)	High. Limited access to AI tools, high initial costs	Moderate. Poor policy inclusion in design codes	Low. Clients prioritise cost minimisation	High. Improved user experience	Moderate. Design innovation interest
Engineers (n=4)	High. System interoperability issues	Low. Less concern with governance	High. Energy savings up to 30%	High. Improved performance data	Moderate. Focus on technical benefits.
Facility Managers (n=3)	Moderate. Maintenance tech skills are lacking	Moderate. Weak standards for O&M	High. Maintenance cost savings (≈20%)	Moderate. Energy reliability improved	High. Sustainability in operations
Urban Planners / Policy Experts (n=3)	Low. Less technical focus	High. Absence of enabling policy frameworks	Moderate. Advocacy for incentive programs	Low. Indirect involvement	High. Interest in policy-driven sustainability

Note. There is a preponderance of insights on technological barriers among architects and engineers. For planners, their main concern borders on policy gaps. Insights on economic incentives occur across all cohorts, while comfort and performance outcomes are interestingly positive. This reinforces data on energy efficiency.

Source: Authors' analysis sheets.

Table 15

Qualitative NVivo Word Frequency/Results on Coding Query

Rank	Term	% Weighted Reference	Associated Theme
1	"Efficiency"	13.2	Economic Incentives
2	"Cost"	12.6	Economic Incentives
3	"Policy"	10.1	Policy Gaps
4	"Training"	8.4	Technological Barriers
5	"Maintenance"	7.9	Technological Barriers
6	"Comfort"	6.8	Comfort & Performance
7	"Sustainability"	6.4	Sustainability Awareness
8	"Energy"	6.1	Economic Incentives
9	"Integration"	4.5	Technological Barriers
10	"Clients"	4.0	Economic Incentives

Note. "Efficiency" and "Cost" dominate the lexical field. This strengthens the fact that performance and economic drivers constitute the vital motivators for AI/IoT adoption.

Source: Authors' analysis sheets.

Table 16

Integration of Quantitative Indicators and Qualitative Evidence on Key Themes Influencing AI/IoT Adoption in Green Buildings.

Theme	Quantitative Indicator	Supporting Qualitative Evidence	Interpretation
Technological Barriers	30% respondents cite a lack of expertise	"Retrofitting is hindered by system interoperability issues." – Engineer	Skill and infrastructure deficits slow adoption
Policy Gaps	Only 20% mention supportive policies.	"There's no clear regulation for smart integration in green codes." – Planner.	Weak policy instruments
Economic Incentives	64% confirm cost savings	"We cut 20% off maintenance costs with predictive maintenance." – Facility Manager.	High potential for cost-based motivation
Comfort & Performance	68% report improved comfort	"Occupants are happier and systems self-adjust." – Architect	Positive user-centred outcomes
Sustainability Awareness	75% acknowledge increased awareness	"Clients are now asking for smart systems." – Architect	Growing cultural shift toward sustainable tech

Note. Data integration of qualitative insights coded in NVivo and quantitative indicators. The highlight is on recurring themes that are impacting the adoption of AI/IoT in GBD.
Source: Authors' analysis sheets.

4.5.4 ***Interpretations:*** There is confirmation by NVivo coding of five (5) dominant themes that are affecting the adoption of AI/IoT in Nigeria's green building. Qualitative results are sufficiently supported by quantitative analysis, as a reduction in energy use (25% - 30%) and comfort improvement (68% - 80%) are identified as the most consistent gains. Triangulated validation is strengthened by the integration of both data types within NVivo, thus increasing significantly the robustness of findings.

5. Discussion

The study has shown that integrating Artificial Intelligence (AI) and Internet of Things (IoT) high-ends into GBD improves economic sustainability through quantifiable reduction in energy use, lowered costs of maintenance, and optimised comfort of the occupants. Empirical data affirms a 25–30% optimisation in energy efficiency and a well-established correlation ($r = 0.82$, $p < 0.01$) between economic performance and the adoption of AI/IoT plexuses. These outcomes corroborate the fact that intelligent technologies can notably ensure the transition of Nigeria to an energy-efficient and cost-effective architecture that supports national sustainability objectives. Irrespective of this bright prospect, varied constraints persist. Barriers in technical contexts, such as deficiencies in infrastructure, a dearth of local expertise, and spiralling initial costs, limit widespread implementation. Weak and/or null policy frameworks and the near-absence of actionable policies on smart buildings further lend their quota in restricting scalability. Furthermore, the sample size, though multifaceted, is constrained to six case study buildings. This could affect transferability. Prospective research should consider the deployment of a broader cross-geographical sample, policy impact assessments, and time-series performance analysis to reinforce the evidence base for a sustainable architecture that is AI/IoT-driven.

6. Conclusion and Recommendations

In conclusion, this study affirms a fact. The incorporation of Artificial Intelligence (AI) and Internet of Things (IoT) technologies in GBD notably improves the economic sustainability of liveable structures. This can be seen through the quantifiable gains in the reduction of costs of maintenance, improved energy efficiency, and optimised well-being of users of such liveable structures. Results informing this assertion include a mean 27% reduction in the consumption of energy, 20% lower maintenance costs, and a 64% savings in expenditure. All these are achievable within the first year of adoption. These results formed inferences from the analysed quantitative dataset. Such evidence further emphasised increased sustainability awareness. This is driven by professionals' acknowledgement of AI/IoT plexuses being the vital indicator for predictive maintenance, adaptive comfort regulation, and long-term return on investment. Nevertheless, technological barriers, weak policy frameworks, limited local expertise, and failure to incentivise intelligent building practices remain issues that have hindered widespread adoption in developing economies.

In view of these precedents, the following recommendations are proffered:

a. Professionals in the built environment, including architects and engineers, should consider the adoption of a hybrid design strategy that merges AI- and IoT-based systems with bioclimatic principles and vernacular nuances to improve and propagate responsiveness and cost-effectiveness with respect to local climatic conditions.
b. Continuous Professional and Development Programs should be intensified to build competence in technical know-how in the integration of smart plexuses.
c. Professional bodies and governments should look towards embedding AI/IoT benchmarks within green certification frameworks and national building codes.
d. The provision of grants and tax incentives for early adopters will also go a long way in motivating adoption.
e. Enforcement of interoperability standards by policies must also ensure compatibility of data across building plexuses.
f. Further longitudinal and cross-regional studies should evaluate the life-cycle economic performance of AI/IoT-enabled buildings and develop localised algorithms tailored to tropical climates.
g. Collaborative studies between academia, industry, and policymakers are needed to evolve a national smart-building roadmap that promotes both sustainability and economic resilience in Nigeria's built environment.

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