PAJRI
PAN-AFRICAN JOURNAL OF RESEARCH AND INNOVATION

Pan-African Journal of Research and Innovation in Environmental, Earth Sciences and Geosciences

ISSN: 3413-9431 | Vol. 1, Issue 1 | www.pajri.com | DOI: https://doi.org/10.0000/0000

Integration of Artificial Intelligence (AI) in Building Performance Optimization.

Oguntimehin Abiodun Sunday, Emehinola Olusola Matthew

[1,2]*Department of Architectural Technology, School of Environmental Studies, Federal Polytechnic, Ilaro, Ogun State*

* Corresponding author: abiodun.oguntimehin@feederalpoly.edu.ng

Received: 2026-09-01	Accepted: 2026-09-03	Published: 2026-09-04

ABSTRACT

The integration of Artificial Intelligence in building performance optimization offers strong opportunities for advancing sustainability in tropical regions where high temperatures and humidity present distinct design challenges. Although interest in this field is growing, only a small number of studies focus on the practical use of AI driven parametric design tools in tropical environments. This study examines how AI algorithms, working with parametric simulation platforms such as Grasshopper and Ladybug, can optimise daylighting, thermal comfort, and energy performance in naturally ventilated buildings in Nigeria. Using machine learning models such as Artificial Neural Networks and Support Vector Machines, several building configurations were assessed across multiple performance indicators. The results show that AI based optimisation improved daylight autonomy by up to 40 percent, reduced energy consumption by 30 percent, and increased thermal comfort hours by 34 percent when compared with conventional design methods. The study concludes that AI supported parametric workflows offer a strong approach for climate responsive and energy efficient building design in data scarce tropical settings. It recommends wider adoption of AI enhanced design processes, increased investment in professional training, and the development of AI models that are tailored to tropical building conditions.

KEYWORDS: Artificial Intelligence, Building Performance Optimization, Daylighting, Energy Efficiency, Machine Learning, Parametric Design, Thermal Comfort, Tropical Climate.

OPEN ACCESS
This is an open-access article distributed under the terms of the Creative Commons Attribution 4.0 International Licence (CC BY 4.0).

1. Introduction

According to Egis (2025), the global construction industry is experiencing a major shift toward data driven design and operation, with Artificial Intelligence becoming an important driver of building performance optimisation. This development is especially relevant in tropical regions such as Nigeria, where rapid urban growth, rising cooling energy demands, and climate related design challenges require new approaches to sustainable building design. Traditional design practices, which depend mainly on manual calculations and static simulations, do not fully capture the changing environmental conditions and complex interactions that influence energy use and occupant comfort in tropical settings (Hong et al., 2018).

AI based technologies provide powerful capabilities through predictive analytics, automated optimisation, and real time adaptive control. By analysing large datasets from environmental sensors, climate records, and occupant behaviour, AI enables architects and engineers to create resilient and adaptive design solutions that respond to changing conditions. These capabilities support the achievement of sustainability goals such as reduced operating costs, lower carbon emissions, and improved environmental responsiveness (Ogunbiyi et al., 2023).

The purpose of this paper is to explore how AI technologies are being applied to optimise building performance in tropical regions, focusing on energy efficiency, thermal comfort, and intelligent system control. It also evaluates the advantages, implementation barriers, and research opportunities that support the integration of AI in sustainable building design and management.

1.1 Statement of Problem

Despite the proven potential of AI in building performance optimisation, important gaps remain in its application within tropical climates. These include:

a. Limited tropical specific research, since most AI applications have been designed for temperate regions and are not fully validated for hot humid tropical conditions.
b. Challenges in integrating AI with parametric design workflows, especially in resource constrained settings.
c. Limited quantitative evidence on the performance gains of AI driven methods in tropical educational buildings.
d. Technical, economic, and institutional barriers that hinder the adoption of AI in developing tropical regions.

2. Literature Review

In a review of machine learning applications in building performance analysis, Deb et al. (2024) noted that as buildings become more complex, the use of AI systems is essential to bridge the performance gap left by traditional static simulation tools, offering crucial support to designers and facility managers. Traditional simulation tools, while effective, rely on pre-defined static models that may not fully represent real-world dynamics. AI technologies bridge this gap by enabling adaptive learning and predictive analytics, which support designers and facility managers in achieving performance goals more efficiently.

In a systematic review of AI applications in sustainable building design, Abanda et al. (2020) found that AI integration in building design promotes efficient decision-making through the use of neural networks and machine learning algorithms that analyse energy use patterns and indoor environmental data. These models are capable of identifying non-linear relationships between environmental variables, such as solar radiation, temperature, and occupancy, which influence energy consumption.

In a primary empirical study, Chan and Wong (2021) emphasised that AI enables multi-objective optimisation of building systems, allowing for real-time adjustments to HVAC operations and occupant comfort. Their work in tropical Asia demonstrated that AI-controlled HVAC systems reduced energy use by approximately 15% compared to conventional control systems. Similarly, Badu et al. (2022) found that the combination of AI-based predictive control and passive design principles significantly reduced cooling loads in office buildings within warm and humid climates.

AI's potential extends beyond operational control to predictive maintenance and lifecycle optimisation. By analysing sensor data and historical trends, AI can anticipate faults in mechanical systems before they occur, preventing energy losses and costly repairs (Yoon et al., 2019). This predictive capacity aligns with sustainable design objectives, ensuring resource efficiency throughout a building's life cycle.

Despite these advances, challenges persist in the application of AI in building performance optimisation. Data availability, model accuracy, and the high cost of system integration remain major barriers in developing countries. In a review of AI applications in the built environment, Yoon et al. (2019) noted that the success of AI models depends largely on the quality of input data and the extent of interdisciplinary collaboration between designers, engineers, and computer scientists. The lack of standardised datasets for tropical contexts often limits the adaptability of AI systems that were initially trained on datasets from temperate regions.

2.1. AI and Passive Design Optimization in Tropical Climates

2.1.1. Daylighting Optimization

Daylighting optimization in tropical regions presents unique challenges because of excessive sun radiation and glare risks. Parametric layout equipment incorporated with AI algorithms permit designers to assess heaps of layout iterations effectively.

In a review of daylighting analysis techniques in tropical climates, Sengupta et al. (2024) examined the effectiveness of Grasshopper and Ladybug gear for daylighting analysis. In a primary optimisation study, Biyik et al. (2020) incorporated genetic algorithms with parametric modeling to optimize window-to-wall ratios and shading configurations, reaching 35% improvement in daylight autonomy while decreasing glare

risk by 40%.

2.1.2. Thermal Comfort in Naturally Ventilated Buildings

Thermal comfort in tropical naturally ventilated buildings depends on complex interactions. Traditional comfort models (e.g., Fanger's PMV) frequently prove insufficient for tropical contexts where occupants exhibit higher adaptive tolerance.

In a review of AI applications in natural ventilation optimisation, Ting et al. (2023) reported that AI-based natural ventilation techniques can optimise thermal comfort in tropical classrooms, with prior studies demonstrating up to a 28% increase in comfortable hours. Agyekum et al. (2022) argued that AI-enhanced simulation tools can identify optimum combinations of passive strategies (orientation, shading, thermal mass, natural ventilation), a capability that conventional design approaches struggle to achieve.

2.2. Barriers to AI Adoption in Tropical Building Design

Despite demonstrated benefits, AI adoption in tropical building design faces significant barriers:

2.2.1. Technical Barriers

Data scarcity: Comprehensive building performance datasets are rare in tropical developing regions.

Model transferability: Models trained on temperate climate data perform poorly when applied to tropical conditions.

Computational requirements: Advanced AI algorithms demand significant computing resources.

2.2.2. Economic Barriers

Owolabi et al. (2019) identified high implementation costs as a primary barrier in the Nigerian construction industry:

- Software licensing fees for parametric design and AI platforms.
- Hardware infrastructure for data collection and processing.
- Training and capacity building for design professionals.

2.2.3. Institutional Barriers

Babatunde and Perera (2020) noted that institutional resistance, lack of regulatory frameworks, and limited interdisciplinary collaboration slow AI diffusion. Professional education programs rarely include AI or computational design training, creating a skills gap.

3. Methodology

This study employed a mixed-method research approach, integrating quantitative simulations with qualitative analysis to investigate the role of Artificial Intelligence (AI) in enhancing building performance within tropical regions, with a specific focus on Nigeria's climatic conditions. The methodology was structured to examine how AI-driven tools can optimise energy use, thermal comfort, and indoor environmental quality across diverse building types.

3.1. Research Design

The research adopted a descriptive and experimental design. The descriptive phase focused on collecting data from existing studies and field measurements related to AI-based performance tools, while the experimental phase utilised simulation models and algorithmic tools to test performance optimisation strategies. The design ensured that real-world parameters from tropical climates, such as high solar radiation, temperature fluctuations, and humidity, were integrated into the modelling process.

3.2. Study Area and Building Sample

The study area was limited to tropical regions, with a focus on Lagos and Ogun States, Nigeria. These areas represent humid equatorial climates, characterised by intense solar gain and high energy demand for cooling. Their selection was based on the need to understand how AI-based design interventions can address environmental and infrastructural challenges unique to the tropics.

The sample comprised 12 naturally ventilated educational buildings (6 primary schools and 6 secondary schools) purposively selected across Lagos and Ogun States. Buildings were selected based on the following criteria:

1. constructed between 1995 and 2015;
2. predominantly naturally ventilated with no mechanical cooling;
3. oriented within 45° of the north-south axis; and
4. in continuous use during the study period.

The sample size of 12 was determined using purposive sampling to ensure typological diversity while remaining feasible for intensive monitoring within resource constraints.

3.3. Data Collection

Data were collected from two primary sources over an 18-month fieldwork period (January 2024 to June 2025):

3.3.1. Primary Data: Field data on indoor temperature, relative humidity, daylight levels, CO~2~ concentration, occupancy, and energy consumption were obtained from the 12 selected educational buildings. The following sensor configurations were deployed:

- **Indoor air temperature and relative humidity:** HOBO UX120-006M data loggers (Onset Computer Corporation), recording at 15-minute intervals with an accuracy of ±0.21°C and ±2.5% RH.
- **Daylight illuminance:** Onset T&D TR-74Ui illuminance loggers, positioned at desk height (0.75 m above floor level) in representative classrooms, recording lux levels at 10-minute intervals.
- **Energy consumption:** IoT-enabled single-phase energy meters (SDM120-Modbus) installed at distribution boards to record real-time electricity use at 15-minute intervals.
- **CO~2~ and occupancy:** Telaire T6703 CO~2~ sensors combined with passive infrared occupancy counters to validate ventilation effectiveness and occupancy-driven load profiles.
- **Outdoor meteorological data:** A Davis Vantage Pro2 weather station installed at each site to record outdoor dry-bulb temperature, relative humidity, global horizontal solar radiation, and wind speed.

Data were downloaded monthly via USB/Bluetooth interfaces and stored in encrypted CSV format. Occupancy surveys were conducted quarterly to validate sensor-based occupancy estimates.

3.3.2. Secondary Data: Relevant literature, simulation databases, and building performance datasets were obtained from credible sources such as published research within 2016–2025. Climate data for Lagos (latitude 6.52°N, longitude 3.38°E) and Abeokuta (latitude 7.15°N, longitude 3.35°E) were extracted from the Nigerian Meteorological Agency (NiMet) archives to validate simulation weather files.

3.4. Data Preprocessing

Prior to model training, the raw dataset underwent systematic preprocessing:

1. **Outlier removal:** Values exceeding ±3 standard deviations from the mean were flagged and removed.
2. **Missing data imputation:** Linear interpolation was applied for gaps shorter than 2 hours; gaps exceeding 2 hours were excluded from training sets. Missing data constituted less than 5% of the total dataset.
3. **Normalization:** Min-Max scaling (0–1 range) was applied to all input features to ensure uniform weighting across variables with different units.
4. **Feature engineering:** Derived variables including solar heat gain coefficient, effective aperture area, and operative temperature were computed from primary measurements.

Simulation and Analytical Tools

Building performance simulations were conducted using parametric modelling software. Rhinoceros 3D served as the modelling platform, with Grasshopper visual scripting interfaced with Ladybug and Honeybee plugins to generate environmental data inputs. EnergyPlus was used as the underlying simulation engine for physics-based thermal and energy calculations.

The primary focus remained on the integration of AI algorithms for predictive optimisation. Machine learning models such as Artificial Neural Networks (ANN) and Support Vector Machines (SVM) were used to predict energy consumption and indoor comfort levels.

Model Inputs (Feature Set):

- Window-to-wall ratio (WWR)

- Building orientation (degrees from north)
- External shading angle (degrees)
- Cross-ventilation opening area (% of floor area)
- Wall U-value (W/m²K)
- Roof U-value (W/m²K)
- Occupancy density (persons/m²)
- Outdoor air temperature (°C)
- Global horizontal solar radiation (W/m²)

Model Outputs (Target Variables):

- Energy Use Intensity (EUI, kWh/m²/year)
- Daylight Autonomy (DA, %)
- Thermal Comfort Hours (% of occupied hours within PMV ±0.5)

Artificial Neural Network (ANN): A feedforward multilayer perceptron was implemented in Python (TensorFlow/Keras). The architecture comprised:

- Input layer: 9 neurons (corresponding to the feature set)
- Hidden layers: 3 layers with 64, 32, and 16 neurons respectively
- Activation function: Rectified Linear Unit (ReLU)
- Output layer: 3 neurons (EUI, DA, thermal comfort hours)
- Optimizer: Adam (adaptive moment estimation)
- Loss function: Mean Squared Error (MSE)
- Training regimen: 80% training, 20% testing split; 5-fold cross-validation; early stopping with a patience of 20 epochs; batch size of 32; maximum 500 epochs.

Support Vector Machine (SVM): A Support Vector Regression (SVR) model was implemented using scikit-learn with the following configuration:

- Kernel: Radial Basis Function (RBF)
- Hyperparameter optimisation: Grid search over C (0.1, 1, 10), epsilon (0.01, 0.1, 1), and gamma (scale, auto)
- Cross-validation: 5-fold CV on the training set

The data were trained and validated using regression-based learning models to assess accuracy. Energy simulations were performed under various orientation, material, and ventilation scenarios to test the performance of AI recommendations. The AI algorithms iteratively adjusted design variables until convergence to an optimal solution was achieved, thereby demonstrating the efficiency of machine learning in improving tropical building design performance.

Model Validation and Evaluation

To ensure reliability, AI-generated outputs were compared with traditional simulation results and field measurements:

1. **Simulation benchmark:** ANN and SVM predictions were compared against EnergyPlus baseline simulations for identical design configurations. The EnergyPlus models were calibrated to within ±10% of measured monthly energy use.

2. **Field validation:** Post-optimisation monitoring was conducted for 3 months (April–June 2025) on 2 pilot buildings to validate AI prediction accuracy against actual performance.
3. **Performance metrics:** Model accuracy was evaluated using:

- Coefficient of determination (R^2)
- Root Mean Square Error (RMSE)
- Mean Absolute Error (MAE)
- Computational processing time (seconds per design variant)

The comparative analysis allowed for the identification of performance gaps and the potential of AI integration for tropical architecture.

4. Ethical Considerations

All building data were anonymised to maintain confidentiality, and no personal or private data were used. The study adhered to the ethical guidelines for environmental research and simulation data handling. Permission for sensor installation and energy data access was obtained from school administrators prior to data collection.

5. Findings and Data Analysis

This study demonstrated the significant performance improvements achieved by using AI-enhanced parametric design workflows for educational buildings in a humid tropical climate. Data analysis was conducted between July 2025 and March 2026, using the complete dataset collected from January 2024 to June 2025.

AI Model Performance

Superior Accuracy: The Artificial Neural Network (ANN) model consistently outperformed the Support Vector Machine (SVM) model across all predictive metrics (R^2 = 0.92–0.94 for ANN vs. R^2 = 0.89–0.91 for SVM). The ANN achieved an RMSE of 3.2 kWh/m²/year for EUI prediction, compared to 4.8 kWh/m²/year for SVM. Thermal comfort hour predictions showed a MAE of 2.1% for ANN versus 3.4% for SVM.

Computational Efficiency: AI-assisted optimization enabled the evaluation of 30,000 design variants in 8 hours, representing a 99.8% reduction in computation time compared to full physics-based simulation (which required approximately 167 hours for an equivalent scope).

Multi-Objective Performance Improvements

AI optimization achieved substantial, simultaneous improvements across all three primary performance metrics compared to the baseline "as-built" design. Results are summarised in Table 1.

Table 1. Multi-Objective Performance Comparison (Baseline vs. AI-Optimized)

Performance Metric	Baseline Performance	AI-Optimized Performance	Improvement
Daylight Autonomy (DA)	38.5%	53.9%	40%
Thermal Comfort Hours	52.3%	70.1%	34%

Energy Use Intensity (EUI)	68.4kWh/m²/yr	47.9kWh/m²/yr	30% Reduction

Note. Baseline derived from as-built simulation calibrated to Authors' field measurement, 2024–2025. AI-optimized values represent Pareto-optimal solutions from the ANN-driven search.

Optimal Design Guidelines

The Sensitivity Analysis and Optimal Configuration Analysis identified the most influential design parameters, providing clear, evidence-based recommendations for tropical educational buildings (Table 2).

Table 2

Optimal Design Parameters from Sensitivity Analysis

Design Parameter	**Optimal Range/Value**	**Key Impact**
Orientation	North-South axis (±15°)	Strongest influence on Thermal Comfort. Minimizes direct solar gain.
External Shading Angle	40°	Optimal balance between 52% Solar Heat Gain Reduction and high Daylight Admission.
Window-to-Wall Ratio (WWR)	42% (Range: 35-45%)	Balances daylight admission (DA ≈54%) and thermal load.
Cross-Ventilation Area	12-15% of floor area	Critical for maximizing comfortable hours through natural ventilation.

Note. Optimal ranges derived from ANN sensitivity analysis validated against EnergyPlus simulations and Authors' field measurement, 2024–2025.

Implications and Contributions

AI as an Integrative Design Tool

Pareto Frontier: The optimization identified over 40 non-dominated solutions, demonstrating AI's capacity to navigate complex design trade-offs and provide designers with a range of high-performing options, rather than just a single "best" answer.

Augmenting Designers: The study concludes that AI's effectiveness relies on human expertise to formulate the problem (objectives and constraints), emphasizing a hybrid approach where AI explores and human judgment selects and refines.

Economic Impact

The economic analysis was conducted as a **scenario-based estimate** derived from the monitored performance data. The following assumptions underpinned the calculation:

Table 3. **Economic Analysis Assumptions**

Parameter	**Assumed Value**	**Source/Justification**
Representative building floor area	2,000 m²	Mean area of sampled schools
Baseline Energy Use Intensity	68.4 kWh/m²/year	Monitored and simulated baseline
Optimized Energy	47.9 kWh/m²/year	AI-optimized output

Use Intensity		
Electricity tariff	₦150/kWh	NERC commercial tariff benchmark, 2024
Capital cost of AI optimization	₦5,500,000	Software licensing, hardware, consultant fees
Annual maintenance cost	₦450,000	8.2% of capital cost
Discount rate	10%	Nigerian construction sector benchmark
Analysis period	20 years	Standard building lifecycle assessment

Calculation Basis:

- Baseline annual energy cost: 68.4 kWh/m²/yr × 2,000 m² × ₦150/kWh = ₦20,520,000
- Optimized annual energy cost: 47.9 kWh/m²/yr × 2,000 m² × ₦150/kWh = ₦14,370,000
- Annual energy cost saving: ₦20,520,000 − ₦14,370,000 = ₦6,150,000 (₦3,075/m²)

For a typical 2,000 m² school, this translates to annual savings of ₦6.15 million (approximately $7,600 USD at 2025 exchange rates). With a capital investment of ₦5.5 million and annual maintenance of ₦450,000, the net simple payback period is:

$$\text{Payback} = \frac{₦5{,}500{,}000}{₦6{,}150{,}000 - ₦450{,}000} = 0.96 \text{ years}$$

Thus, the cost of design optimization is recovered in less than one year, after which the school accrues net annual savings of approximately ₦5.7 million.

Barriers to Adoption

Data Scarcity and the Skills Gap (integrating architectural design, building physics, and machine learning) are the most significant practical barriers to broader AI adoption in resource-constrained tropical contexts.

Conclusion

Summary of Key Findings

This study investigated the integration of Artificial Intelligence (AI) with parametric design tools for optimizing building performance in tropical climates, specifically focusing on naturally ventilated educational buildings in Nigeria.

Key Results

Table 4. Summary of Performance Improvements

Performance Metric	Baseline → AI-Optimized	Improvement / Reduction
Daylight Autonomy	38.5% → 53.9%	40% Improvement
Thermal Comfort Hours	52.3% → 70.1%	34% Increase
Energy Use Intensity (EUI)	68.4→ 47.9 kWh/m²/year	30% Reduction

Note. Baseline values derived from as-built simulation calibrated to Authors' field measurement, 2024–2025.

Design and Computational Insights

Optimal Design Parameters: North-south building orientation (±15°), WWR of 40–45%, external shading at 35–45° angles, and cross-ventilation openings of 12–15% of floor area.

Computational Efficiency: AI reduced design evaluation time by 99.8%, enabling exploration of 200 times more design variants than conventional parametric workflows.

Model Validation: Field monitoring conducted between April and June 2025 confirmed AI prediction accuracy within 7% for key performance metrics, supporting practical reliability.

Recommendations

1. Architectural designers should integrate AI for rapid exploration and physics-based parametric simulation for validation.
2. There should be installation of IoT sensors in AI-designed buildings to validate performance against predictions and refine future AI models.
3. Architectural engineers should update architecture and engineering programs to include Grasshopper/Ladybug, building physics simulation, and machine learning fundamentals.
4. There should be professional networks for knowledge sharing on AI applications to accelerate knowledge diffusion.
5. There should be establishment of multi-institutional collaborations to create publicly accessible datasets for AI model training.

6. Conclusion

The integration of Artificial Intelligence with parametric design tools represents a significant advancement in tropical building performance optimization. The recommendations provide a roadmap for this transformation, ensuring that as tropical regions face challenges from climate change and urbanization, AI-enhanced design can create buildings that are simultaneously comfortable, efficient, and sustainable.

Contributions to Knowledge

This paper makes several important contributions:

Empirical contribution: Provides quantitative evidence of AI effectiveness in tropical building contexts, addressing a significant gap in literature dominated by temperate climate studies.

Methodological contribution: Demonstrates a practical integration pathway for AI with parametric design tools accessible to design practitioners.

Practical contribution: Establishes evidence-based design guidelines for tropical educational buildings.

References

Abanda, F. H., Ebohon, O. J., & Tah, J. H. M. (2020). Applications of artificial intelligence and machine learning in sustainable building design: A review. *Energy and Buildings*, *219*, Article 110034. https://doi.org/10.1016/j.enbuild.2020.110034

Agyekum, K., Armah, H., Agyemang, S., Nkansah, A., Darkwah, B. A., & Agbemah, T. (2022). Integrating artificial intelligence into building performance simulation for optimized passive design. *Smart and Sustainable Built Environment*, *11*(2), 221–240. https://doi.org/10.1108/SASBE-03-2021-0043

Babatunde, O. M., & Perera, S. (2020). Challenges and prospects of artificial intelligence in building performance optimization. *Energy and Buildings*, *216*, Article 110196. https://doi.org/10.1016/j.enbuild.2020.110196

Badu, S., Fröbel, M., & Völzke, F. (2022). Reducing cooling loads in office buildings in warm and humid climates: Synergy of passive design and AI-based predictive control. *Energy and Buildings*, *273*, Article 112411. https://doi.org/10.1016/j.enbuild.2022.112411

Biyik, E., Karagöz, Y., Eke, H., & Yücesu, S. (2020). Optimization of window-to-wall ratio and shading design for energy-efficient building envelope in hot-humid climate using genetic algorithm. *Energy Conversion and Management*, *218*, Article 113009. https://doi.org/10.1016/j.enconman.2020.113009

Chan, M. T., & Wong, L. Y. (2021). Multi-objective optimization of building energy systems using deep reinforcement learning in tropical climate. *Energy and AI*, *6*, Article 100109. https://doi.org/10.1016/j.enai.2021.100109

Deb, C., Ozcelik, Y., Ayyub, M., & Khoshbakht, M. (2024). A review of the application of machine learning in building performance analysis and prediction. *Energy and Buildings*, *299*, Article 113601. https://doi.org/10.1016/j.enbuild.2023.113601

Egis. (2025). *From data to possibility: The AI opportunity in construction*. Egis Group. https://www.egis-group.com/all-insights/from-data-to-possibility-the-ai-opportunity-in-construction

Hong, T., Langevin, J., & Sun, K. (2018). Building simulation: Ten challenges. *Building Simulation*, *11*(5), 871–898. https://doi.org/10.1007/s12273-018-0444-x

Ogunbiyi, O. O., Abimbola, S. M., Oyelakin, I. O., Arilesere, T. M., & Ogunbiyi, A. O. (2023). A review of the applications of artificial intelligence in sustainable built environment. *Journal of Engineering Research*, *30*(4), 1–17.

Owolabi, J. D., Faleye, D., Eshofonie, E. E., Tunji-Olayeni, P. F., & Afolabi, A. O. (2019). Barriers and drivers of innovation in the Nigerian construction industry. *International Journal of Mechanical Engineering and Technology*, *10*(3), 334–339.

Sengupta, A., Chathuranganie, G., & Peiris, H. M. (2024). A review of daylighting analysis techniques in tropical climates with an emphasis on integrated design. *Solar Energy*, *270*, Article 112316. https://doi.org/10.1016/j.solener.2024.112316

Ting, Y., Ye, X., Jiang, Y., & Wei, X. (2023). A review of artificial intelligence in optimizing natural ventilation for thermal comfort in buildings. *Building and Environment*, *228*, Article 109849. https://doi.org/10.1016/j.buildenv.2022.109849

Yoon, T., Han, Y., & Cho, J. (2019). Predictive maintenance of building mechanical systems using machine learning and sensor data. *Automation in Construction*, *106*, Article 102871. https://doi.org/10.1016/j.autcon.2019.102871