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Artificial Intelligence in Tropical Building Performance: A Systematic Literature Review

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ABSTRACT

This Systematic Literature Review (SLR) explores the integration of Artificial Intelligence (AI) technologies in building performance research within tropical climates, which are characterized by high temperatures, humidity, and solar radiation. These environmental conditions present challenges for achieving energy efficiency and occupant comfort. The review, guided by the PRISMA framework and structured using the PICO model, synthesizes findings from 56 peer-reviewed articles published between 2015 and 2025. It aims to identify the types of AI technologies employed, their specific applications, and the challenges and opportunities associated with their implementation in tropical building contexts. The analysis reveals increasing adoption of AI in domains such as indoor environmental quality (IEQ), energy consumption, HVAC optimization, and daylighting. Techniques such as machine learning, deep learning, neural networks, and expert systems are commonly used for predictive modelling, simulation, and real-time control. AI has demonstrated significant potential in enhancing building performance, enabling more adaptive and efficient systems. However, the review also identifies several limitations. These include the scarcity of high-quality, localized data in tropical regions, limited generalizability of AI models across diverse building types, and the lack of integration with real-time building management systems. Daylighting and passive design strategies remain underexplored, and there is a need for more occupant-centric approaches. To address these gaps, future research should focus on hybrid modelling techniques, explainable AI, and the development of open-access datasets. Collaboration among researchers and policymakers can translate AI research into context-specific tools and standards supporting SDGs 7, 11, and 13 for sustainable tropical buildings.

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1. Introduction

The built environment sector has undergone significant transformation in recent decades due to increasing global concern over energy consumption, climate change, and sustainable development. Buildings account for a substantial share of global energy use and carbon emissions, especially in regions where extreme climate conditions necessitate intensive heating, cooling, and ventilation. While substantial research has been devoted to improving building performance in temperate and cold climates, strategies and modelling approaches developed in those contexts often cannot be directly applied to tropical regions due to distinct climatic and socio-environmental conditions. Tropical climates which are characterised by consistently high temperatures, high humidity, and intense solar radiation, pose unique challenges for ensuring energy-efficient building performance while maintaining indoor environmental comfort for occupants.

To address these challenges, there is an urgent need for intelligent, adaptive, and data-driven strategies that can optimize various aspects of building performance, including daylighting, energy consumption, HVAC efficiency, and indoor environmental quality (IEQ). In this context, Artificial Intelligence (AI) has emerged as a transformative tool, enabling advanced modelling, prediction, and optimisation processes that can outperform conventional methods.

AI technologies such as machine learning, deep learning, neural networks, expert systems, fuzzy logic, and genetic algorithms are increasingly being deployed in building performance research to discover or analyse patterns in complex datasets, automate decision-making, enhance predictive accuracy, and improve building control systems. Applications of AI range from dynamic energy modelling and real-time building management to smart shading systems and daylight-responsive design strategies. However, most of these applications have been concentrated in non-tropical contexts such as predictive control of HVAC systems in European office buildings or thermal comfort modelling in North American housing, where climatic variability and seasonal changes differ significantly from equatorial conditions.

In contrast, tropical regions such as Southeast Asia, Central Africa, and parts of South America experience persistently high humidity and solar exposure year-round, resulting in distinct energy demand profiles dominated by cooling loads. For instance, air-conditioning alone accounts for up to 50–60% of total electricity use in Malaysian commercial buildings. Despite such energy intensity, few studies have systematically examined how AI can be leveraged to address daylighting optimization, passive cooling, and adaptive comfort specific to tropical environments. This imbalance underscores a significant research gap: tropical regions not only contribute substantially to future global urban growth but also face acute energy and comfort challenges that require localized, data-driven solutions. Understanding what AI technologies are being used, how they are applied, and what limitations or opportunities exist in tropical climate research is essential for advancing sustainable building practices in this region. This Systematic Literature Review (SLR) seeks to address these gaps by providing a comprehensive overview of AI applications in building performance research in tropical climates. This SLR is structured around three core objectives:

1. To provide a comprehensive overview of the current applications of AI technologies in building performance research in tropical climates.
2. To identify key challenges in the implementation, modelling, and validation of AI systems in tropical building performance contexts.
3. To highlight research gaps and propose areas for further investigation.

2. Methodology

A systematic literature search was conducted to investigate empirical evidence on the application of AI technologies in building performance research within tropical climate contexts. The review aimed to explore how AI has been utilised to address energy, thermal, daylighting, and indoor environmental challenges in buildings located in hot and humid regions. The identification and evaluation of relevant studies were guided by the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework (Page et al., 2021). PRISMA method was used as it provides a transparent and replicable framework for conducting systematic literature reviews, particularly suitable for interdisciplinary topics. Other review approaches such as narrative reviews, bibliometric analyses, or meta-analyses were not adopted because they lack the structured screening and eligibility process and require large quantitative datasets with comparable metrics, which are limited in this emerging research area.

The PRISMA methodology comprises four key phases to ensure a systematic and transparent review process: (1) Identification, where a structured combination of keywords is used to search scientific databases for potentially relevant studies; (2) Screening, in which duplicates and clearly unrelated articles are excluded based on titles and abstracts; (3) Eligibility, involving a detailed assessment of full-text articles to determine their relevance and alignment with the inclusion criteria; and (4) Inclusion, where the final set of studies is confirmed for comprehensive analysis (Moher et al., 2010).

2.1 Area Preliminary Phase

This review is guided by the following research question using PICO framework to clearly define the scope and focus: What type of AI technologies are currently being used in building performance research in tropical climate, and what are the key challenges and opportunities? The Population (P) refers to building performance studies specifically conducted within tropical climate contexts, where environmental conditions such as heat, humidity, and solar exposure significantly impact indoor comfort and energy use. The Intervention (I) involves the application of AI technologies, including but not limited to machine learning, deep learning, and expert systems, as tools to enhance building performance. As this review takes an exploratory and synthesizing approach, there is no direct Comparison (C) group included. The Outcome (O) centres on the identification of the types of AI employed, their specific applications in building performance domains, and the key challenges and opportunities reported across the reviewed studies. Table 1 shows the summary of the PICO framework.

Table 1 PICO framework

PICO	Criteria
Population	Building performance studies in tropical climates
Intervention	Use of AI technologies
Comparison	Not applicable as this is an exploratory synthesis
Outcome	Identification of AI types, applications, challenges, and opportunities

To enhance the precision and relevance of the review, a thoughtfully selected set of keywords was utilised. These keywords are curated through titles and abstracts from retrieved articles and further explore with a thesaurus and systematically placed in a logic grid table as shown in Table 2.

Table 2 Keywords identification and logic grid table

Building Performance	Tropical Climate	AI Technologies
Energy	Tropics	Artificial Intelligence
Thermal	Tropical	AI
Daylighting	Hot and Humid	Machine Learning
Indoor Environmental Quality	Equatorial Zone	Deep Learning
HVAC	Wet Equatorial	Neural Network
Envelope	Humid Equatorial	Knowledge Engineering
Comfort	Equatorial Climate	Robotics
		Expert System

2.2 *Identification*

To systematically capture relevant literature, a targeted search string was developed and applied in major academic databases such as Scopus and Web of Science. Both databases were chosen as they are two of the most recognised and reputable academic databases which contain extensive coverage of good quality and peer-reviewed literatures. Scopus provides broader coverage of conference proceedings and emerging journals, which is particularly valuable for capturing the rapidly evolving intersection of AI and building performance studies. WoS, on the other hand, offers more selective indexing with a stronger emphasis on high-impact journals, ensuring the inclusion of well-established research. The combination of both databases thus ensures comprehensive and balanced data collection, reducing the risk of publication bias. The string is formulated to cover keywords related to building performance, AI technologies, and tropical climate contexts as shown in Table 3: TITLE-ABS-KEY (((building) AND (energy OR thermal OR daylighting OR "indoor environment quality" OR hvac OR envelope OR comfort) AND ("tropical climate" OR tropic* OR "hot and humid" OR equatorial) AND ("artificial intelligence" OR ai OR "machine learn*" OR "deep learn*" OR "neural network" OR "knowledge engineer*" OR robotics OR "expert system"))). The use of wildcards (e.g., `tropic*`, `learn*`) ensures inclusion of variations, while Boolean operators (`AND`, `OR`) refine the scope to include interdisciplinary research.

Table 3 Search string development

Database	Search String
SCOPUS	TITLE-ABS-KEY (((building) AND (energy OR thermal OR daylighting OR "indoor environment quality" OR hvac OR envelope OR comfort) AND ("tropical climate" OR tropic* OR "hot and humid" OR equatorial) AND ("artificial intelligence" OR ai OR "machine learn*" OR "deep learn*" OR "neural network" OR "knowledge engineer*" OR robotics OR "expert system")))
Web of Science	TS=((building) AND (energy OR thermal OR daylighting OR “indoor environment quality” OR HVAC OR envelope OR comfort) AND (“tropical climate” OR tropic* OR “hot and humid” OR equatorial) AND (“artificial intelligence” OR ai OR “machine learn*” OR “deep learn*” OR “neural network” OR “knowledge engineer*” OR robotics OR “expert system”))

2.3 *Screening*

The initial search was conducted on May 7, 2025. The above-mentioned search strategy resulted in 138 results from Scopus and 134 results from WoS. To ensure the relevance, reliability, and scholarly rigour of the studies selected for this systematic literature review, a clearly defined set of inclusion and exclusion criteria was established as shown in Table 4. These criteria served to filter and refined the search results during the screening and eligibility phases.

In terms of document type, only peer-reviewed academic journal articles were included in this review, as they represent high-quality, validated research contributions that have undergone critical assessment by experts in the field. Other types of documents such as master's dissertations, book chapters, conference proceedings, editorials, prefaces, and opinion papers were excluded due to their varied levels of academic scrutiny and inconsistent methodological reporting, which may affect the reliability and generalisability of the findings. For the publication year, the review focused on studies published between 2015 and 2025, capturing a contemporary understanding of the integration of AI technologies in building performance research. Studies published before 2015 were excluded to maintain the relevance of the findings, as the development and adoption of AI in the built environment have accelerated significantly in the past decade. In terms of language, only studies published in English were considered. This decision was made to ensure consistency in interpretation and analysis, and due to the limited access to translation resources for non-English publications. While this may result in the exclusion of some valuable studies, English remains the dominant language in international scientific publishing, particularly in the fields of engineering, architecture, and computer science. Finally, studies that were conducted in non-tropical climate zones, or that did not explicitly consider climatic context in relation to AI applications, were excluded to maintain the geographic and thematic focus of the review. Hence, the number of results were reduced to 75 for SCOPUS and 96 for WoS database.

Table 4 Inclusion and exclusion criteria

Criterion	Inclusion	Exclusion
Types of documents	Academic articles	Master dissertations, books chapters, conference proceedings papers, prefaces and opinions
Year	Between 2025 and 2015	Outside the specified year range
Language	English	Other than English
Research area	Building performance Tropical climate	Not related to building performance Other than tropical climate

Duplicate records across databases were identified and removed using Mendeley's built-in detection tool, resulting in 117 unique articles. These were then subjected to a two-stage screening process. In the first stage, titles, abstracts, and keywords were independently screened by two reviewers to ensure alignment with the review objectives. Any discrepancies or uncertainties were resolved through discussion until consensus was reached.

The second stage involved a full-text eligibility assessment to verify the inclusion of only those studies focusing on AI applications in building performance within tropical climates. This includes domains such as energy efficiency, thermal comfort, daylighting, HVAC optimization, and indoor environmental quality. Following this rigorous screening process, 56 studies were retained for the final review. A summary of the workflow is shown in Figure 1.

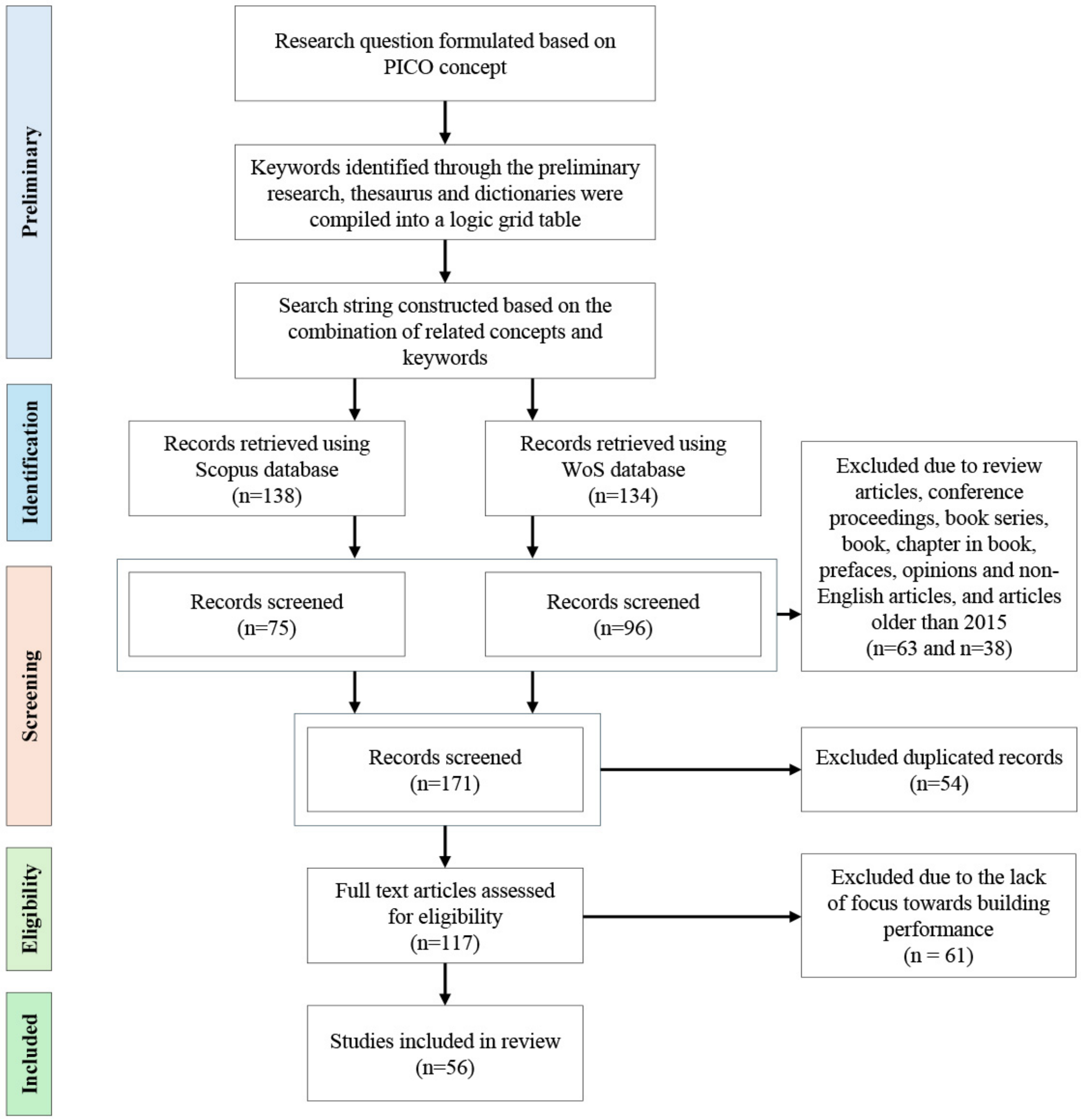

Figure 1 Overview of the study selection process following the PRISMA guidelines

2.4 Analysis

As illustrated in Figure 2, the number of publications on the application of AI in building performance research within tropical climates has increased notably over the past decade. Between 2015 and 2020, publication activity was minimal, with no more than two articles per year and even zero publications in 2016. However, beginning in 2021, the field began to show signs of growth. A significant surge occurred from 2022 onwards, with publication counts rising to 12 in 2022, 9 in 2023, and peaking at 15 in 2024, indicating heightened scholarly attention. Although 2025 is still ongoing, 4 studies have already been published, suggesting that research in this area continues to expand.

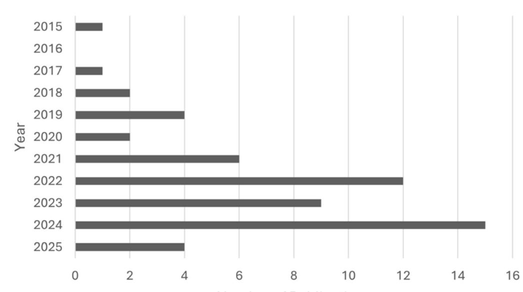

Figure 2 Publication trends of selected literature from 2015 to 2025.

As depicted in Figure 3, most publications originate from Singapore, leading with 10 publications. Singapore's leading contribution is attributed to its national emphasis on smart and sustainable urban development, supported by policies such as the Smart Nation initiative and the BCA Green Mark scheme. This is followed by India (7), Mexico (6), and China (6), indicating significant research contributions from both Asia and Latin America. Malaysia contributed 5 publications, while Iran followed closely with 4. Other contributors include Brazil (3) along with Indonesia and Canada, each with 2 publications. Several other countries such as Denmark, Djibouti, France, Italy, Lebanon, Panama, Saudi Arabia, South Korea, Sri Lanka, the United Arab Emirates, the United States, and Vietnam each contributed a single publication. Although these contributions are limited in number, they demonstrate a geographically diverse but thematically focused engagement with AI applications in building performance. This pattern underscores the global significance of the topic while highlighting a more concentrated research effort in regions characterized by tropical and subtropical climates.

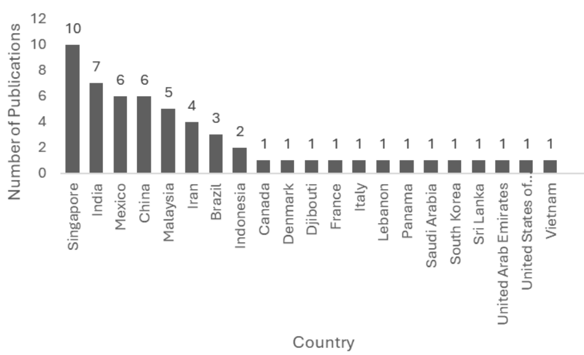

Figure 3 Number of publications by country of origin.

The reviewed literature on AI applications in tropical building performance reveals varying levels of research focus across different performance aspects as shown in Figure 4. Indoor Air Quality (IAQ) emerges as the most extensively studied topic, with 26 publications addressing AI-driven strategies for maintaining healthy and comfortable indoor environments. Energy consumption follows closely, with 23 studies exploring AI's role in optimizing energy use, reducing waste, and improving overall building efficiency. Heating, Ventilation, and Air Conditioning (HVAC) systems are also a significant area of AI application, with 11 publications dedicated to enhancing HVAC performance through intelligent control, predictive maintenance, and adaptive system design. In contrast, daylighting, despite its critical importance for occupant comfort and energy savings in tropical climates, appears underrepresented with only 5 publications focusing on AI-enabled daylighting strategies and modelling. The strong research focus on IAQ reflects the growing concern over health, comfort, and ventilation efficiency in densely populated tropical regions, where high humidity and pollution levels pose persistent challenges. In contrast, daylighting remains less explored due to its complex interaction with tropical glare and heat gain, which complicates AI modelling and data acquisition compared to mechanical systems like HVAC.

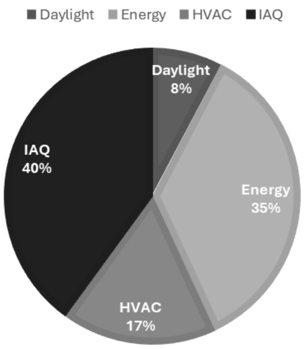

Figure 4 Distribution of publications by research focus.

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3 Discussion

3.1 Daylight

3.1.1 Methodologies, AI Techniques, and Models in Daylight Performance

The methodologies adopted across the five reviewed studies reflect a comprehensive and evolving approach to integrating AI into building performance optimisation. All studies begin with a simulation-based modelling phase, using tools such as EnergyPlus, Radiance, and DesignBuilder to simulate energy consumption, daylighting, and thermal comfort under various design and environmental conditions. Parametric modelling platforms like Rhino3D and Grasshopper, often enhanced with Ladybug and Honeybee plugins, are used to systematically vary design parameters such as window-to-wall ratio, shading geometry, glazing type, and building orientation. In studies addressing climate change, future weather data are generated using morphing techniques or Representative Concentration Pathways and Shared Socioeconomic Pathways (Yan et al., 2022; Zou et al., 2021).

To reduce the computational burden of full-scale simulations during optimisation, three studies (Yan et al., 2022; Zhang & Ji, 2022; Zou et al., 2021) employ Artificial Neural Networks (ANN) as surrogate models. These ANN are trained on large datasets, often exceeding tens of thousands of samples, to predict performance metrics such as energy use intensity, useful daylight illuminance, and predicted mean vote. The models are validated using standard metrics like root mean square error (RMSE), mean absolute error (MBE), and coefficient of determination (R^2), with most achieving R^2 values above 0.95, indicating high predictive accuracy. Zou et al. (2021) implement their ANN models using TensorFlow, while Zhang and Ji (2022) utilise MATLAB for backpropagation neural networks.

In contrast, Fan et al. (2023) and Nicoletti et al. (2023) extend AI applications to real-time control and comfort prediction. The former uses a Radial Basis Function neural network to predict integrated daylight and thermal comfort in passive gymnasiums, based on field-measured environmental data and occupant surveys. The latter develops a feedforward ANN to control the slat angles of Venetian blinds in real time, using inputs such as solar altitude, azimuth, irradiance, occupancy, and seasonal mode. Their model, trained on over 200,000 data points, is

validated across multiple cities and orientations, demonstrating strong generalizability and robustness.
Multi-objective optimisation is a central component in four of the studies, where evolutionary algorithms, particularly the Non-dominated Sorting Genetic Algorithm II, are used to balance competing objectives such as minimizing energy use and discomfort hours while maximizing daylight availability or visual comfort. These optimisations are either performed directly on simulation outputs or via surrogate models, enabling efficient exploration of complex design spaces. Yan et al. (2022) further enhances model adaptability through transfer learning, fine-tuning an XGBoost model trained on one building type for application to another, thereby reducing the need for retraining and expanding the model's applicability.

3.1.2 Climate Adaptation and Future Weather Scenarios in Daylight Design

Daylight performance is inherently sensitive to climatic conditions, particularly solar radiation patterns, cloud cover, and atmospheric clarity, all of which are expected to shift under climate change. The integration of future weather scenarios into daylight modelling is therefore essential for resilient building design. Zou et al. (2021) addressed this by incorporating Representative Concentration Pathways 4.5 and 8.5 into their optimisation framework for a classroom in Guangzhou. Using morphed weather files to simulate future decades, they found that while UDI values remained relatively stable, the optimal design strategies for daylighting, such as shading type and window orientation, shifted significantly. For example, egg-crate shading devices became more favourable under warmer scenarios due to their ability to balance daylight access and solar heat gain. Similarly, Yan et al. (2022) used Shared Socioeconomic Pathway (SSP2-4.5) scenarios to simulate future climates in Singapore and found that although UDI was less sensitive to climate change than thermal comfort or energy use, design adaptations were still necessary to maintain visual comfort. These findings underscore the importance of using AI models trained on future climate data to anticipate changes in daylight availability and to guide the design of buildings that remain comfortable and energy-efficient over their entire lifecycle.

3.1.3 Limitations and Future Research Directions in AI for Daylight Performance

Despite the promising applications of AI in daylight performance modelling, several limitations remain that constrain its broader adoption and effectiveness. One major challenge is the dependency of AI models on the quality and diversity of training data. For daylight modelling, this includes accurate simulation of solar positions, sky conditions, and interior surface reflectance. Nicoletti et al. (2023) acknowledged that their ANN model was trained on a specific case study and may not generalise well to other buildings or shading systems without retraining. Another limitation is the lack of real-world validation. Most models are trained and tested on simulated data, which, while comprehensive, may not fully capture the variability of actual daylight conditions or occupant responses. Incorporating real-time sensor data and occupant feedback could enhance model robustness and applicability. Furthermore, integration with dynamic building systems, such as automated lighting and shading controls, remains underexplored. While Nicoletti et al. (2023) demonstrated a real-time control application, broader integration with internet of things (IoT) platforms and building management systems is still limited. Additionally, most studies focus on standard daylight metrics like UDI and glare indices, leaving out more nuanced indicators such as circadian lighting or user satisfaction. Future research should explore hybrid AI models, real-time daylight monitoring, and adaptive control systems to fully leverage AI's potential in daylight-responsive design. Expanding the scope of performance metrics and validating models in diverse real-world settings will be crucial for advancing the field.

3.2 Energy

3.2.1 Methodologies, AI Techniques, and Models in Building Energy Performance

The methodologies employed across the 22 reviewed articles reflect a multidisciplinary approach to enhancing the building energy performance in tropical climates, with a strong emphasis on AI, simulation modelling, and empirical validation. A significant number of studies utilised ANN to model and predict energy consumption patterns, optimize building systems, and assess occupant behaviour. For instance, ANN models were developed to estimate monthly electrical energy consumption in Malaysian households based on techno-socioeconomic factors, achieving high accuracy and interpretability (Sena et al., 2021). Similarly, ANN frameworks were applied to predict energy use in school buildings in Saudi Arabia and to optimize the control of Venetian blinds for energy efficiency and visual comfort (Alshibani, 2020; Nicoletti et al., 2023). Complementing these were machine learning (ML) techniques such as ensemble learning and deep learning models, including Long Short-Term Memory (LSTM) networks, which were used to forecast photovoltaic (PV) performance and residential electricity demand under varying climatic conditions (Liang et al., 2024; Sena et al., 2021).

Simulation-based modeling was another cornerstone methodology, with tools like EnergyPlus and DesignBuilder extensively used to simulate building energy performance under different design configurations and climate scenarios. These simulations enabled detailed assessments of the impact of envelope materials, HVAC systems, and shading strategies on energy use and thermal comfort (Alshibani, 2020; Nutkiewicz et al., 2022). Optimisation algorithms, particularly Genetic Algorithms (GAs) and NSGA-II, were frequently integrated with simulation and AI models to identify optimal design parameters. These were used to optimize insulation thickness, phase change material integration, and window properties for energy savings and thermal comfort (Baghoolizadeh et al., 2023; Nutkiewicz et al., 2022; Zou et al., 2021).

Several studies incorporated future climate scenario modelling using Representative Concentration Pathways or Shared

Socioeconomic Pathways to assess building performance under projected weather conditions. Morphing techniques were employed to generate future hourly weather data, allowing researchers to evaluate the resilience of building designs in cities like Singapore and Mumbai (Nutkiewicz et al., 2022; Zou et al., 2021). Control strategies such as Model Predictive Control and reinforcement learning were also explored to optimize HVAC operations and enhance energy flexibility in net-zero buildings, often supported by digital twins and real-time sensor data (Mengual Torres et al., 2022).

Empirical data collection played a crucial role in many studies, with field surveys, sensor networks, and IoT-based monitoring systems used to gather real-time data on energy use and indoor environmental conditions. These data were essential for model calibration and validation, particularly in studies focusing on informal settlements and social housing (Mendez-Monroy et al., 2022; Nutkiewicz et al., 2022; Yan et al., 2022). Finally, model performance was consistently evaluated using statistical metrics such as RMSE, Mean Absolute Percentage Error, Coefficient of Determination (R^2), and MBE, ensuring the reliability and robustness of predictive and optimisation models(Nicoletti et al., 2023; Nutkiewicz et al., 2022; Qavidelfardi et al., 2022; Sena et al., 2021; Wan Roshdan et al., 2024; Zou et al., 2021).

3.2.2 Research Gaps and Future Directions

Despite the growing adoption of AI and ML techniques in building energy modelling, several research gaps remain that warrant further investigation. One of the most prominent gaps is the limited generalizability of AI models across different building types and climatic contexts. Many studies, such as those by Sena et al. (2021) and Nicoletti et al. (2023), focused on specific building categories such as residential or educational and relied on localized datasets, which may limit the transferability of their models to other settings. Although some efforts have been made to apply transfer learning and ensemble methods, there is still a need for more robust frameworks that can adapt to diverse building typologies and operational conditions, particularly in data-scarce tropical regions.

Another critical gap lies in the integration of AI models with real-time control systems. While several studies demonstrated the predictive capabilities of ANNs and LSTM networks, fewer explored their deployment in live building management systems for dynamic energy optimisation (Liang et al., 2024; Sankara kumar et al., 2024). The potential of reinforcement learning and digital twins for real-time decision-making remains underutilised. Furthermore, the majority of the AI applications in the reviewed literature focused on energy consumption prediction, with less emphasis on multi-objective optimisation that simultaneously considers thermal comfort, indoor air quality, and occupant satisfaction.

Data quality and availability also pose significant challenges. Many models were trained on simulated data or limited field measurements, which may not capture the full variability of real-world conditions. Ahmed et al. (2025) and Mendez-Monroy et al. (2022) emphasized the importance of empirical data collection through IoT systems and surveys, yet the integration of such data into AI pipelines is still in its infancy. Additionally, standardization in model validation is lacking. Although metrics like RMSE, MAPE, and R^2 were commonly used, there is no consensus on benchmark datasets or performance thresholds, making cross-study comparisons difficult.

Future research should prioritize the development of hybrid models that combine physics-based simulations with data-driven AI approaches to leverage the strengths of both paradigms. There is also a need for open-access datasets and collaborative platforms that facilitate model sharing and benchmarking. Moreover, expanding the scope of AI applications to include adaptive control, fault detection, and occupant-centric design will enhance the practical relevance of these technologies. As tropical regions face increasing energy demands and climate variability, advancing AI-driven building energy modelling will be crucial for achieving sustainable and resilient built environments.

3.3 IEQ

3.3.1 Methodologies, AI Techniques, and Models in IEQ

The 15 reviewed studies on IEQ in tropical climates employed a range of methodologies that integrate empirical data collection, simulation modelling, and advanced AI and ML techniques. Most studies began with field measurements of environmental parameters such as indoor air temperature, humidity, CO_2 levels, and outdoor weather conditions (Aguilera et al., 2019; He et al., 2021). Several also captured occupant behaviours, including window and fan usage, thermal sensation votes, and physiological signals (Payet et al., 2022). Data preprocessing was a critical step in model development. Techniques such as one-hot encoding, normalisation, and outlier detection were commonly used (Abeyrathna et al., 2024; Jiao & Tan, 2024; Tekler et al., 2024). To address class imbalance, synthetic data generation using Conditional Tabular GAN was applied to augment underrepresented categories (Jiao & Tan, 2024). Feature selection methods, including variance filtering and Random Forest importance scores, helped refine input variables (Abeyrathna et al., 2024).

A variety of ML models were employed, including Decision Trees, Random Forests, Support Vector Machines, and ANN, with Feedforward Neural Networks showing strong predictive performance (Abeyrathna et al., 2024; Aguilera et al., 2019; Dai et al., 2023; Ibiapino & de Alencar Nääs, 2024; Jamei et al., 2022; Jiao & Tan, 2024; Mohite & Surawar, 2024; Payet et al., 2022). Deep learning models such as Convolutional Neural Networks (CNN) and Transformer-based architectures were used to capture complex spatial and temporal patterns (Jiao & Tan, 2024). Transfer learning was a key strategy for adapting models to data-scarce tropical regions, while reinforcement learning was used for real-time HVAC and window control (Chen et al., 2018). Model training and evaluation followed standard practices, including cross-validation, hyperparameter tuning, and performance metrics such as accuracy, F1-score, RMSE, and R^2 (Abeyrathna et al., 2024; Jiao & Tan, 2024). Simulation tools like EnergyPlus and IDA-ICE were used to validate models and test performance under different climatic scenarios (Aguilera et al., 2019; He et al., 2021). Some studies incorporated subjective feedback and physiological data to enhance personalization.

Overall, the reviewed studies underscore the versatility and effectiveness of AI and ML in enhancing IEQ. From predictive modelling and occupant behaviour analysis to real-time control and passive design optimisation, these techniques offer robust tools for improving indoor environments in tropical regions.

3.3.2 Data Challenges and Transfer Learning Applications in IEQ

One of the most pressing challenges in applying AI to IEQ research in tropical climates is the scarcity and imbalance of high-quality, labelled data. Many tropical regions lack long-term, granular datasets on indoor air quality, occupant behaviour, and thermal comfort, which are essential for training robust machine learning models. This limitation has led researchers to explore innovative solutions such as transfer learning, data augmentation, and synthetic data generation.

Transfer learning has proven particularly effective in addressing data scarcity. Jiao & Tan (2024) introduced a CNN-ConvTrans model that leverages transductive transfer learning to predict thermal comfort in West Bengal using source data from global datasets like ASHRAE RP-884. Their model achieved a 60.2% accuracy despite limited target domain data, demonstrating the potential of transfer learning to generalize across climates and building types. Similarly, Payet et al. (2022) tackled the challenge of missing occupancy data by estimating occupant presence using plug load energy consumption and regression decision trees. This approach enabled the development of behaviour models for window and fan use in a tropical office building, even in the absence of direct occupancy sensors. To further mitigate data imbalance, Jiao & Tan (2024) employed Conditional Tabular GANs to synthetically generate underrepresented thermal sensation classes. This technique improved model performance across all categories, especially in predicting extreme comfort levels, which are often under-sampled in real-world datasets. Aguilera et al. (2019) also addressed data limitations by using simple building descriptors and weather data to predict indoor air temperature. Their decision tree model achieved 92% accuracy under known conditions, offering a lightweight solution for mobile-based thermal comfort estimation in data-scarce environments.

These studies highlight the importance of creative data strategies in tropical IEQ research. Whether through transfer learning, synthetic data generation, or proxy variable estimation, AI models can be adapted to perform well even when traditional datasets are incomplete or imbalanced.

3.3.3 Research Gaps and Future Directions

Despite the growing application of AI and ML in IEQ research, several critical gaps remain—particularly in the context of tropical climates. These gaps span data availability, model generalizability, integration with real-time systems, and the inclusion of human-centric design principles.

A recurring limitation across the reviewed studies is the scarcity of high-quality, longitudinal datasets from tropical regions. Many AI models, such as those developed by Abeyrathna et al. (2024) and Aguilera et al. (2019), rely on relatively short-term or simulated data, which may not capture seasonal variations or long-term occupant behaviour. This data limitation restricts the robustness and adaptability of predictive models, especially when applied to diverse building types and climates. To address this, Aguilera et al. (2019) introduced a transfer learning strategy that leverages large-scale datasets from other regions to improve model performance in data-scarce tropical settings. However, while promising, such approaches require further validation across different cultural and climatic contexts to ensure generalizability.

Another gap lies in the limited integration of subjective occupant feedback into AI models. Most studies, including Payet et al. (2022), focus on environmental parameters (e.g., temperature, humidity, CO_2) or physiological signals, but few incorporate real-time subjective comfort responses. This omission can lead to models that are technically accurate but misaligned with actual occupant satisfaction.

Moreover, while several studies have demonstrated the potential of AI for real-time control—such as reinforcement learning for HVAC optimisation (Chen et al., 2018)—few have tested these systems in live operational environments. The transition from simulation to deployment remains a significant hurdle, requiring collaboration between AI developers, building engineers, and facility managers.

There is also a lack of research on the intersection of AI and passive design strategies. Studies on green roofs and evapotranspiration provide valuable insights into passive cooling, but AI-driven optimisation of such systems is still underexplored. Future research could investigate how AI can dynamically manage irrigation, shading, and vegetation to enhance IEQ while minimizing resource use (Chaudhuri et al., 2019; Chen et al., 2018; He et al., 2021; Liu et al., 2021; López-Pérez & Flores-Prieto, 2023).

Finally, the challenge of model interpretability persists. While complex models like CNNs and Transformers offer high accuracy, their "black-box" nature can hinder adoption in practice. There is a need for explainable AI approaches that provide actionable insights to designers, operators, and occupants.

3.4 HVAC

3.4.1 Methodologies, AI Techniques, and Models in HVAC

Several studies on HVAC utilised ML and AI techniques to model energy consumption and predict cooling loads. Kondath et al. (2024) applied deep learning architectures such as CNN, LSTM, and Sequence-to-Sequence models for day-ahead cooling load forecasting in tropical commercial buildings. Similarly, Bekdaş et al. (2023) used ensemble learning methods including Gradient Boosting and Stacking to predict cooling loads based on building design features. Jiang et al. (2023) introduced a hybrid approach combining Deep Belief Networks with an Improved Snake Optimisation Algorithm to enhance load forecasting accuracy. These models were trained on large datasets derived from simulations or field measurements, emphasizing the importance of data preprocessing and feature selection.

ANNs were a common modelling tool across multiple studies. Seo et al. (2022) and Lopes and Lamberts (2023) used ANNs to optimize HVAC control and predict energy consumption, respectively. López-Pérez and Flores-Prieto (2023) extended this by comparing ANN, fuzzy logic, and adaptive neuro-fuzzy inference systems for adaptive thermal comfort modelling. These models were validated using statistical metrics such as R^2, MAE, and RMSE, and were often integrated into control frameworks for real-time HVAC operation.

Experimental validation was central to several studies. Chen et al. (2018) developed a prototype Enhanced Dehumidification Air Conditioning system and tested it under various seasonal conditions using a multi-evaporator DX configuration. Chaudhuri et al. (2019) conducted controlled experiments using wearable sensors to collect physiological data for comfort prediction. Liu et al. (2021) performed a large-scale field study across 34 households in China, collecting environmental and behavioural data to train predictive models using ANN and Gradient Boosting Decision Trees.

Simulation-based methodologies were also prominent. Lopes and Lamberts (2023) used EnergyPlus to generate 250,000 simulations for training a metamodel to predict HVAC energy use across different climates. López-Pérez and Flores-Prieto (2023) employed TRNSYS to simulate annual cooling loads and evaluate energy savings from various comfort models. Bekdaş et al. (2023) used Monte Carlo simulations and BIM tools to create a synthetic dataset for ML training.

Control strategies varied from rule-based to optimisation-driven approaches. Chaudhuri et al. (2019) introduced the Optimal Air Temperature algorithm, integrating comfort prediction with ANN-based energy modelling. Chen et al. (2018) implemented a five-status control logic in their EDAC system, enabling flexible operation without complex supplementary systems. Jiang et al. (2023) used an optimisation algorithm to fine-tune HVAC operation based on forecasted loads.

In summary, the methodologies across these studies reflect a multidisciplinary approach combining AI, experimental science, simulation, and control engineering. This integration enables more accurate, adaptive, and energy-efficient HVAC systems tailored to occupant comfort and climatic conditions.

3.4.2 Research Gaps and Future Directions

While significant progress has been made, several research gaps remain. Most studies focus on specific building types or climates, limiting generalizability. There is a need for longitudinal studies that capture seasonal and behavioural variability over time. Integration of renewable energy sources and smart grid compatibility remains underexplored. Real-time adaptive systems leveraging IoT and edge computing offer promising avenues for future research. Standardization of datasets and benchmarking protocols would facilitate model comparison and replication. Finally, more interdisciplinary collaboration is needed to bridge the gap between engineering, data science, and human-centred design in HVAC research (López-Pérez and Flores-Prieto, 2023; Liu et al., 2021; Chaudhuri et al., 2019; Chen et al., 2018).

4 Conclusion

This SLR has provided a comprehensive examination of the application of AI in building performance research within tropical climates. These regions face distinct environmental challenges, including high humidity, intense solar radiation, and elevated temperatures, which necessitate innovative and adaptive solutions for energy efficiency and occupant comfort. The review highlights a growing body of scholarly work that leverages AI technologies, such as machine learning, deep learning, and neural networks, to optimize energy consumption, enhance IEQ, improve HVAC performance, and develop daylight-responsive design strategies.

The analysis of 56 peer-reviewed studies published between 2015 and 2025 reveals a notable increase in research activity, particularly in recent years. AI has been successfully integrated into simulation modelling, predictive analytics, and real-time control systems, demonstrating its potential to transform building operations and design. However, the adoption of AI in tropical building contexts remains uneven. While energy and IEQ have received considerable attention, areas such as daylighting and passive design strategies are underrepresented. Moreover, many AI models are developed using localized or simulated datasets, which limits their generalizability across different building types and climatic conditions.

Across the four domains examined, several overarching themes emerge. AI applications in tropical building performance remain largely fragmented, often focusing on individual performance metrics rather than adopting a holistic approach to building operation. Common methodological limitations include an overreliance on simulated datasets, limited generalisability across different climatic and building typologies, and insufficient validation in real-world tropical settings. Persistent challenges include the scarcity of high-quality tropical datasets, limited integration of AI with real-time building management systems, and the complexity and interpretability of AI algorithms. While approaches such as transfer learning, reinforcement learning, and hybrid modelling show promise, they remain underutilized. Furthermore, the absence of standardized benchmarks and validation protocols continues to hinder cross-study comparisons and the practical implementation of AI solutions.

To advance the field, future research should focus on developing open-access datasets and collaborative platforms that support model sharing and benchmarking. Integrating AI with IoT technologies and smart building systems can enable real-time adaptive control and enhance operational efficiency. There is also a need to explore occupant-centric and passive design strategies through AI, ensuring that building performance improvements align with human comfort and sustainability goals. Furthermore, adopting explainable AI approaches will be crucial for fostering trust and facilitating the practical adoption of these technologies by designers, engineers, and facility managers.

In conclusion, AI holds significant promise for addressing the complex challenges of building performance in tropical climates. By bridging current research gaps and embracing interdisciplinary collaboration, the built environment sector can move toward more resilient, energy-efficient, and climate-responsive buildings that support global sustainability objectives and improve the quality of life for occupants which aligns closely with several United Nations Sustainable Development Goals (SDGs) such as SDG 7 (Affordable and Clean Energy), SDG 11 (Sustainable Cities and Communities), and SDG 13 (Climate Action).

This review establishes that AI-driven modelling and optimization have already demonstrated measurable benefits in enhancing energy performance and indoor environmental quality in tropical buildings. However, the limited availability of contextual data, lack of standardized evaluation frameworks, and underrepresentation of passive and occupant-focused strategies remain key challenges. Moving forward, research must prioritize the creation of open tropical datasets, integration of explainable and hybrid AI models, and stronger collaboration between building designers, AI experts, and policymakers to translate technological advances into scalable, sustainable, and context-sensitive building solutions.

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Conflicts of Interest

The author(s) declare(s) that there is no conflict of interest regarding the publication of this paper

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