IKR Publishers

IKR Journal of Engineering and Technology (IKRJET)
Journal homepage: https://ikrpublishers.com/ikrjet/
Volume-2, Issue-4 (July-August) 2026

OPEN ACCESS
ISSN: 3107-7331 (Online)

AI-Augmented Passive Architectural Design for Thermally Resilient Housing in Nigeria Through Structured Review and Conceptual Framework

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DOI: *10.5281/zenodo.22132584*

ARTICLE INFO

Article history:
Received : 12-08-2026
Accepted : 20-08-2026
Available online : 27-08-2026

Citation: Ajayi, T. O., Ayodele, T. S., & Akeredolu, O. U. (2026). AI-Augmented Passive Architectural Design for Thermally Resilient Housing in Nigeria Through Structured Review and Conceptual Framework. *IKR Journal of Engineering and Technology (IKRJET)*, *2*(4), 136-154.

ABSTRACT **Review Article**

For this review, thermal resilience is operationally defined as the capacity of housing to limit indoor heat exposure and dependence on mechanical cooling while maintaining feasible opportunities for occupant adaptation under climatic, electricity-supply and affordability constraints. Thermal resilience is therefore treated as broader than thermal comfort alone. This critical structured narrative review synthesises peer-reviewed analytical studies, supplemented by standards, policy documents, institutional reports and seminal background sources. Scopus and Google Scholar served as the principal literature-discovery sources, supplemented by targeted searches of publisher platforms, including ScienceDirect, Taylor & Francis Online and MDPI-hosted journals, and relevant institutional websites and repositories. The final search was completed on 30 July 2026. Evidence was coded under passive architectural design, adaptive thermal comfort, AI-enabled analytics, urban cooling, planning integration, affordability and governance. Across the reviewed evidence, climate-specific shading, natural ventilation, roof and envelope measures, landscape strategies and occupant adaptation are recurrent performance themes. At the same time, uncertainty arises from limited Nigerian measured datasets and the transferability of models developed in other climates. AI is treated as transparent decision support for comparing architectural and neighbourhood alternatives against comfort, overheating, energy, cost and liveability criteria, with local calibration and post-occupancy validation. The article develops an architecture-led, planning-integrated workflow linking climate intelligence, passive design, simulation, AI-assisted optimisation and performance-in-use feedback.

Keywords: Artificial Intelligence, Passive Design, Thermal Resilience, Adaptive Thermal Comfort, Building Performance Simulation, Climate-Responsive Housing, Nigeria.

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Introduction

Rising heat exposure, electricity constraints and household affordability make thermal performance a major housing-design concern in Nigeria (Adaji et al., 2019; Nigerian Meteorological Agency [NiMet], 2026; Ochedi & Taki, 2022). Residential comfort is shaped by solar gain, humidity, ventilation, roof and envelope performance, urban form, user control and access to passive or mechanical cooling (Adaji et al., 2019; Hong et al., 2017; Ochedi & Taki, 2022). Nigerian field evidence and warm-climate guidance therefore support design strategies that reduce unwanted heat gain while retaining opportunities for occupant adaptation before mechanical cooling is introduced (Adaji et al., 2019; Ochedi & Taki, 2022; UNEP, 2021).

Building-sector evidence connects housing design with climate mitigation, energy demand and heat-health risk.

Cabeza et al. (2022) identify buildings as a major source of greenhouse-gas emissions, while the International Energy Agency (IEA), United Nations Environment Programme (UNEP) and Global Alliance for Buildings and Construction (GlobalABC) identify demand reduction, efficient envelopes and low-carbon cooling among transition priorities (Cabeza et al., 2022; IEA, 2025; UNEP & GlobalABC, 2026). In warm climates, high indoor temperatures can also increase heat-related health risks, making passive heat reduction relevant to both energy and health outcomes (UNEP, 2021; World Health Organization [WHO], 2018).

Nigeria spans hot-humid, hot-dry and composite climatic conditions, and its housing sector operates within energy-access and affordability constraints that affect cooling choices (Energy Transition Office, 2022; NiMet, 2026; Ochedi & Taki, 2022). Nigeria's Energy Transition Plan provides a broader national decarbonisation policy context, while the National Building Energy Efficiency Code provides more direct guidance for energy-efficient building design (Energy Transition Office, 2022; Federal Ministry of Power, Works and Housing [FMPWH], 2017; Geissler et al., 2018). Passive design literature similarly locates early decisions in site, orientation, form, roof, envelope, shading, openings, vegetation and occupant use before additional cooling energy is introduced (Energy Sector Management Assistance Program [ESMAP], 2020; UNEP, 2021).

AI- and data-driven methods can extend this workflow through energy and comfort prediction, performance analytics and optimisation, while building-performance simulation, airflow modelling, remote sensing and post-occupancy analytics provide complementary computational approaches for systematically comparing design alternatives (Amasyali & El-Gohary, 2018; Merabet et al., 2021; Nguyen et al., 2014; Wang & Srinivasan, 2017; Wei et al., 2018). Across AI and building-performance literature, however, the reliability of model-supported decisions depends on data quality, boundary conditions, occupancy assumptions, validation and transparent human oversight rather than on algorithmic output alone (Amasyali & El-Gohary, 2018; Bourdeau et al., 2019; OECD, 2024; UNESCO, 2021).

Within the corpus reviewed here, passive-design and thermal-comfort research is more developed than evidence integrating these domains with AI-supported decision-making in Nigerian housing. Nigerian comfort and residential-performance studies are geographically limited compared with the wider international evidence base, while data-driven models are sensitive to training context, occupancy assumptions and climatic transferability (Adaji et al., 2019; Amasyali & El-Gohary, 2018; Bourdeau et al., 2019; Ochedi & Taki, 2022). The resulting evidence gap is the limited empirical basis for determining whether AI-assisted and simulation-supported design recommendations developed from international or geographically restricted datasets remain valid across Nigerian climatic conditions, construction systems and naturally ventilated or mixed-mode housing.

The review therefore asks: (1) which passive strategies are most relevant to thermal resilience in Nigerian housing; (2) how can AI and simulation improve early-stage architectural decisions; (3) what limitations arise when comfort and prediction models are transferred into Nigerian contexts; and (4) what validation and governance practices are required for responsible implementation?

The article therefore proposes an architecture-led, planning-integrated conceptual performance framework that connects climate data, passive architectural design, adaptive comfort, computational simulation, AI-assisted option testing and post-occupancy learning, while explicitly recognising the need for subsequent empirical validation in Nigerian housing. The synthesis foregrounds design variables that architects can specify, simulate and evaluate while integrating urban and regional planning considerations where settlement form, development control, landscape, infrastructure and neighbourhood heat shape housing performance.

Review Design and Analytical Procedure

A critical structured narrative review was adopted because the subject spans architecture, building science, thermal comfort, urban and regional planning, urban climate and AI governance. Narrative synthesis permits comparison of heterogeneous measured, simulated, survey-based and conceptual evidence that cannot be pooled meaningfully into a single effect estimate, while explicit search and appraisal procedures improve transparency (Baumeister & Leary, 1997; Green et al., 2006; Grant & Booth, 2009; Ferrari, 2015; Snyder, 2019).

Literature discovery was undertaken principally through Scopus and Google Scholar and supplemented by targeted publisher-platform and institutional searches. For reproducibility, the complete source-specific search strings, search dates, search fields and any result-screening limits are reported in Supplementary Table S1. The final search was completed on 30 July 2026. Search terms were organised into thematic blocks covering passive design and cooling, adaptive thermal comfort, AI and machine learning in building performance, simulation-based optimisation, Nigerian and warm-climate housing, urban cooling, post-occupancy evaluation and responsible AI; source-specific Boolean combinations are provided in Supplementary Table S1.

The review emphasised literature published from 2000 to 30 July 2026 to capture contemporary developments in building-performance simulation, AI and thermal-comfort research, while earlier seminal works on bioclimatic design and thermal comfort were retained where conceptually necessary. Sources were considered relevant where they addressed residential buildings, or warm-climate building evidence with explicit applicability to passive design, thermal comfort, building-performance prediction or optimisation, urban cooling, professional implementation or governance. Transferability to Nigeria was subsequently treated as an appraisal criterion rather than assumed at inclusion.

Screening proceeded through title review, abstract assessment and full-text relevance checking. The review was purposive and iterative rather than protocol-registered and is therefore reported as a structured narrative synthesis rather than a PRISMA-compliant systematic review. Peer-reviewed analytical studies were synthesised separately from methodology papers, standards, policy documents, institutional reports and seminal background texts so that empirical findings were not conflated with methodological guidance, policy positions or conceptual evidence.

The extraction matrix recorded author, year, study location, climatic context, building type, study design, variables, analytical tools, principal findings, reported limitations and relevance to Nigeria. A condensed study-characteristics and evidence-appraisal matrix is presented in Table 1 to make the synthesis traceable to the reviewed literature. Evidence was coded under passive architectural design, adaptive comfort, AI analytics, urban cooling, housing affordability, planning integration and governance. Because the review did not apply a formal risk-of-bias scoring instrument, sources were qualitatively appraised for methodological clarity, contextual relevance, data transparency, validation procedures, recency and source authority. These criteria informed interpretation and transferability judgements rather than a numerical quality score.

The synthesis is interpretive and does not estimate pooled effect sizes. It distinguishes evidence of technical possibility from evidence of measured housing performance and uses that distinction to formulate a framework for future empirical testing in Nigerian dwellings.

Table 1: Characteristics and critical appraisal of core analytical evidence used in the synthesis

Study	**Context /scale**	**Evidence type or method**	**Principal focus used in this review**	**Contribution to the synthesis**	**Critical limitation/transferability to Nigerian housing**
Adaji et al. (2019).	Abuja/Nigerian residential context; low- and middle-income housing	Field-based indoor comfort and occupant-adaptation study; dry-season evidence	Indoor thermal conditions, occupant adaptation and naturally ventilated residential comfort	Provides direct Nigerian measured evidence supporting adaptive interpretation of residential comfort and the importance of occupant behaviour.	High contextual relevance, but geographically and seasonally bounded; dry-season evidence from a single urban context cannot establish nationwide or year-round performance.
Abdulkareem & Al-Maiyah (2025).	Abuja affordable housing	Nigerian affordable-housing passive-design study	Passive interventions and improvement of the residential thermal environment	Provides recent Nigerian evidence that passive-design modifications can improve thermal conditions in affordable housing.	Directly relevant but Abuja-specific; the present review does not report sufficient methodological detail to establish transferability across Nigerian climatic zones or housing types.
Ochedi& Taki (2022).	Nigerian residential buildings	Framework/design-oriented energy-efficiency study	Climate-responsive envelope and passive strategies for Nigerian housing	Provides a Nigerian design framework connecting passive architectural decisions with comfort and energy performance.	Strong contextual design relevance, but framework/design evidence should not be treated as equivalent to multi-location longitudinal measured performance.
Aflaki et al. (2015).	Tropical climates; building façades and openings	Review of natural-ventilation applications	Façade openings, natural ventilation and tropical passive cooling	Establishes the importance of opening configuration and façade design for ventilation-led cooling in tropical buildings.	Secondary international evidence; effectiveness remains dependent on local wind, security, noise, dust, insect protection and occupant operation.
Harkouss et al. (2018).	Multiple climatic contexts	Passive-design optimisation study	Climate-specific optimisation of low-energy building design	Demonstrates that optimal passive-design configurations vary by climatic context rather than conforming to a universal prototype.	International and optimisation-based; input assumptions, construction systems and occupant profiles may differ substantially from Nigerian housing.
Hu et al. (2023).	Residential buildings in hot climates	Systematic review	Effects of passive design on indoor thermal comfort and energy savings	Supplies broad comparative evidence that passive measures can improve comfort and reduce energy demand in hot-climate housing.	Secondary evidence aggregates heterogeneous climates, building types and methodologies; reported effects should not be transferred directly to Nigerian dwellings without local validation.

Liu et al. (2020).	Hot-humid Hong Kong residential buildings	Future-climate building-performance assessment	Passive strategies under climate-change conditions	Supports consideration of future overheating and climate robustness rather than optimisation only for current weather conditions.	Climatically informative but geographically, morphologically and technologically different from Nigerian residential contexts.
Li et al. (2018)	Urban scale	Comparative urban-heat mitigation analysis	Cool roofs and green roofs as urban heat-island mitigation strategies	Supports integration of building-surface interventions with neighbourhood-scale thermal-resilience planning.	Primarily urban/outdoor heat evidence; reductions in urban temperature do not automatically quantify indoor residential comfort benefits.
Norton et al. (2015).	Urban landscapes	Planning framework for green infrastructure	Prioritisation of vegetation and green infrastructure for urban cooling	Supports the manuscript's planning component linking tree canopy, green infrastructure and heat-responsive development control.	Planning-scale evidence rather than dwelling-level performance evidence; effects are highly dependent on urban morphology and local meteorology.
Perini & Magliocco (2014).	Urban environment	Analysis of vegetation, density, building height and atmospheric conditions	Local temperature and outdoor thermal-comfort interactions	Demonstrates the interaction of urban morphology and vegetation in shaping local thermal conditions.	International urban evidence; direct translation to indoor Nigerian housing performance requires additional building-scale measurement.
Ziter et al. (2019).	Urban landscape	Empirical assessment of canopy–impervious-surface interactions	Tree canopy and impervious surfaces as determinants of daytime urban heat	Supports neighbourhood-scale cooling and the manuscript's tree-canopy/permeability indicators.	Concerns outdoor urban heat rather than indoor housing comfort; magnitude and spatial scale of effects are context dependent.
Amasyali& El-Gohary (2018).	Building-energy studies across multiple contexts	Review of data-driven energy-prediction studies	Data-driven/ML building-energy prediction, inputs and evaluation	Establishes the potential of data-driven prediction while emphasising dependence on training data, features and evaluation procedures.	Secondary and predominantly international; does not demonstrate that externally trained models are valid for Nigerian housing.
Bourdeau et al. (2019).	Multiple building contexts	Review of data-driven modelling and forecasting	Model selection, forecasting and data dependence	Supports the manuscript's caution that apparently precise model outputs may remain uncertain when input data and boundary conditions are weak.	Methodological evidence rather than Nigerian application evidence; transferability depends on local data quality and validation.
Wang & Srinivasan (2017).	Building-energy prediction literature	Review comparing AI prediction approaches	Capabilities of single and ensemble AI models	Supports use of AI for building-energy prediction and model comparison.	Secondary methodological evidence; predictive capability does not demonstrate architectural suitability or climatic transferability to Nigeria.
Wei et al. (2018).	Building-energy literature	Review of data-driven prediction and classification approaches	Data-driven prediction/classification of building-energy performance	Reinforces the role of machine learning in prediction and highlights sensitivity to dataset and model choice.	Broad methodological evidence; not a substitute for locally calibrated Nigerian housing datasets.
Merabet et al. (2021).	Intelligent building-control literature	Systematic review of AI-assisted control techniques	AI-assisted thermal-comfort and energy-efficiency control	Extends the AI component beyond static prediction to intelligent building operation and thermal-comfort management.	Much of the evidence concerns controlled/intelligent building systems; applicability to naturally ventilated or low-resource Nigerian housing may be limited.
Nguyen et al. (2014).	Building-performance analysis	Review of simulation-based optimisation methods	Simulation-supported comparison and optimisation of design alternatives	Supports early-stage comparison of orientation, envelope, glazing and other performance-sensitive design decisions.	Simulation-based optimisation is not inherently AI; outputs remain assumption-sensitive and require contextual calibration and professional interpretation.

Attia et al. (2013).	Building-design process	Assessment of building-performance optimisation tools	Integration of optimisation tools into design decision-making	Supports the need to integrate performance analysis during design rather than treating simulation as a late-stage verification exercise.	Not Nigeria-specific and oriented toward high-performance/net-zero design contexts; workflow implications are more transferable than numerical performance results.
Coakley et al. (2014).	Building-energy simulation	Review of calibration methods	Matching simulated building performance to measured data	Provides methodological justification for calibration, error checking and measured-performance comparison.	Primarily methodological; calibration criteria must be adapted to the variables, monitoring resolution and operating modes of Nigerian housing studies.
Hajdukiewicz et al. (2024).	Naturally ventilated built environments	Narrative review of credible CFD modelling	Geometry, boundary conditions, mesh quality and CFD validation	Provides methodological safeguards for airflow and natural-ventilation analysis.	Secondary evidence; CFD credibility does not remove the need for field measurements, especially under variable Nigerian wind and occupancy conditions.
Hong et al. (2017).	Buildings across multiple contexts	Review of occupant behaviour in buildings	Occupancy, user controls and behaviour-model assumptions	Demonstrates that occupant behaviour can strongly alter the gap between assumed and actual building performance.	General building evidence; behavioural patterns, electricity reliability and household practices must be measured locally rather than transferred directly.
Yan et al. (2015).	Building-performance simulation	State-of-the-art occupant-behaviour modelling review	Representation of occupants within simulation	Supports the manuscript's argument that assumed occupancy profiles can materially affect predicted performance.	Methodological rather than Nigerian field evidence; locally representative schedules and control behaviour remain necessary.
Li et al. (2021)	Building-performance design and operation	Occupant-centric KPI development	Occupant-centred performance indicators	Supports linking design and operation with measurable occupant-centred indicators rather than energy outcomes alone.	KPI framework requires contextual selection and does not itself establish Nigerian comfort thresholds or acceptability limits.
O'Brien et al. (2017).	Building performance	Occupant-centric performance-metrics study	Metrics connecting occupancy and building performance	Supports use of comfort, occupancy and performance-in-use indicators in design evaluation and post-occupancy assessment.	Primarily methodological; metric selection must reflect building mode, available measurements and local comfort criteria.

Note: The table distinguishes direct Nigerian evidence, transferable warm-climate evidence, and methodological or secondary evidence. It does not assign a numerical risk-of-bias score because the review used qualitative appraisal rather than a formal risk-of-bias instrument. Nigerian field and residential studies were given greater contextual weight for conclusions about local comfort and housing performance. In contrast, international studies and methodological reviews were used principally to identify design principles, analytical methods, validation requirements and potential transferability constraints. This distinction is important because the manuscript itself finds that Nigerian measured studies are geographically more limited than the wider international evidence base.

Table 1 demonstrates an important asymmetry in the evidence base. Nigerian studies provide the strongest contextual relevance but remain limited in geographical, seasonal and methodological coverage. In contrast, the international literature offers greater methodological breadth in passive-design optimisation, urban cooling, AI prediction, simulation calibration and occupant modelling. Consequently, the synthesis does not assume direct transferability of externally developed models or quantified performance effects. Instead, international evidence is used to identify candidate strategies and analytical procedures that require local weather data, Nigerian occupancy assumptions, professional review and empirical validation before implementation.

Climate-Responsive Architecture, Planning and Thermal Comfort

Climate-responsive housing design integrates orientation, building form, envelope performance, shading, daylighting, ventilation, materials, landscaping and occupant control in response to local climate. Passive design uses these measures to limit heat gain, support heat dissipation and improve comfort with little or no mechanical energy input (Aflaki et al., 2015; Givoni, 1998; Koenigsberger et al., 1974; Li et al., 2018; Ochedi & Taki, 2022; Olgyay, 1963; Ziter et al., 2019). In warm Nigerian contexts, relevant strategies include solar shading, cross-ventilation, reflective or insulated roofs, courtyards or verandas, vegetation, suitable building depth and material choices that moderate heat flow (ESMAP, 2020; Ochedi & Taki, 2022; UNEP, 2021).

ASHRAE Standard 55 defines thermal comfort in relation to occupants' satisfaction with the thermal environment, while the PMV/PPD model predicts group thermal sensation and dissatisfaction under specified environmental and personal conditions (ASHRAE, 2023; Djongyang et al., 2010; Fanger, 1970; International Organization for Standardization [ISO], 2025). For occupant-controlled naturally conditioned spaces, adaptive approaches are particularly relevant because acceptable conditions reflect prevailing climatic conditions and opportunities for behavioural adjustment; they may also inform mixed-mode buildings during eligible periods when mechanical cooling is not operating (ASHRAE, 2023; de Dear & Brager, 2002; Nicol & Humphreys, 2002). Accordingly, naturally ventilated Nigerian dwellings, and eligible naturally conditioned periods in mixed-mode dwellings, should be assessed using operative temperature, air movement, relevant moisture conditions, occupant control and climatic expectation rather than a single fixed air-temperature target. This distinction is especially pertinent where natural ventilation, fans and intermittent air-conditioning are combined in response to weather, electricity availability and household preferences (Adaji et al., 2019; Hong et al., 2017; Ochedi & Taki, 2022).

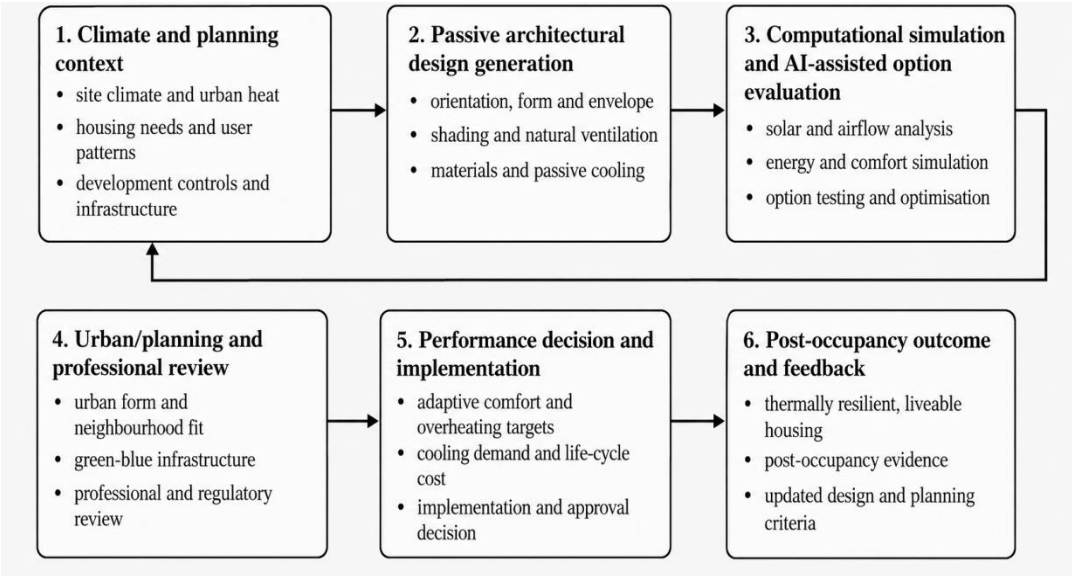

Figure 1: Proposed iterative architecture-led framework for passive housing design, computational evaluation, AI-assisted decision support, planning integration and post-occupancy feedback.

Broader sustainable housing-performance assessment considers thermal comfort alongside energy demand, carbon emissions, indoor environmental quality, affordability, occupant-centred performance and resilience (IEA, 2025; Cabeza et al., 2022; Li et al., 2021; Mulliner et al., 2013; O'Brien et al., 2017; WHO, 2018). For Nigerian housing, these dimensions connect reduced overheating and cooling demand with household expenditure, health, infrastructure pressure and neighbourhood microclimate, while Sustainable Development Goal 11 situates housing within the wider objective of inclusive, safe, resilient and sustainable human settlements (IEA, 2025; Cabeza et al., 2022; United Nations Department of Economic and Social Affairs, n.d.; WHO, 2018).

In this review, AI augmentation refers specifically to the use of data-driven or learning-based methods for prediction, classification, surrogate modelling, optimisation and pattern recognition in support of building and neighbourhood performance decisions. Sensors, building-energy simulation, computational fluid dynamics (CFD), geographic information systems (GIS) and conventional parametric analysis are treated as complementary computational and data-acquisition tools rather than as AI in themselves. Relevant AI-based applications include machine-learning prediction of energy and comfort performance and data-driven option ranking, while simulation-based optimisation and post-occupancy analytics provide complementary means of testing and refining architectural alternatives (Amasyali & El-Gohary, 2018; Attia et al., 2013; Li et al., 2021; Nguyen et al., 2014; Wei et al., 2018). Used together, these methods can support architects and urban and regional planners in evaluating design and neighbourhood alternatives, but their outputs should inform rather than replace professional judgement. Responsible implementation therefore requires transparent assumptions, appropriate validation, accountability and continued human oversight (OECD, 2024; UNESCO, 2021).

Nigerian Climate, Urban Form and Housing Performance

Global evidence establishes buildings and construction as important contributors to energy demand and emissions; for this review, the more immediate implication is that Nigerian housing requires demand-reduction strategies that respond simultaneously to heat exposure, constrained energy access and household affordability (IEA, 2025; Cabeza et al., 2022; UNEP & Global ABC, 2026). This shifts attention from cooling as an equipment-dependent response towards architectural and planning measures that moderate heat gain and reduce cooling demand.

Heat risk is shaped jointly by outdoor climatic exposure and indoor environmental conditions. Urban form, vegetation, surface characteristics and building-envelope performance influence local heat exposure, while high indoor temperatures can increase health risks (Norton et al., 2015; Santamouris, 2014; UN-Habitat, 2024; UNEP, 2021; WHO, 2018). Consequently, thermal resilience requires coordinated assessment of building-scale and neighbourhood-scale conditions rather than treating cooling as an equipment-only problem.

Nigeria encompasses materially different climatic conditions, including hot-humid, hot-dry and transitional/composite environments. Climatic exposure, urban form, electricity reliability and household cooling opportunities also vary across locations (Energy Transition Office, 2022; NiMet, 2026; Ochedi & Taki, 2022). The Nigerian Building Energy Efficiency Code and the Energy Transition Plan provide policy bases for energy-efficient and passive building measures (Energy Transition Office, 2022; FMPWH, 2017; Geissler et al., 2018). Passive-design recommendations should therefore be tied to locally representative weather data, climatic conditions, building characteristics and occupancy assumptions rather than applied uniformly nationwide.

The limited Nigerian residential evidence nevertheless supports integrating passive measures with occupant-centred performance assessment. Field evidence from Abuja demonstrates adaptive responses to indoor thermal conditions, while Nigerian residential-design studies associate envelope and passive interventions with improved comfort and energy performance (Abdulkareem & Al-Maiyah, 2025; Adaji et al., 2019; Ochedi & Taki, 2022). These findings support evaluating passive measures against monitored or appropriately simulated thermal conditions, local occupancy patterns and practical constraints before wider application across Nigerian housing contexts.

Passive Architectural Design Strategies for Thermal Resilience

Foundational bioclimatic literature and recent hot-climate studies identify passive design as a demand-reduction approach that can precede and reduce reliance on mechanical cooling. Its effectiveness depends on interactions among solar geometry, wind, humidity, thermal mass, envelope properties, shading, ventilation, occupant adaptation and local climatic conditions rather than on a universal design prototype (Chenvidyakarn, 2007; Givoni, 1998; Harkouss et al., 2018; Hu et al., 2023; Hyde, 2000; Koenigsberger et al., 1974; Liu et al., 2020; Olgyay, 1963).

Table 2: Illustrative climate-sensitive passive-design priorities applicable to Nigerian housing, subject to local validation

Context condition	Main thermal challenge	Priority passive response	Computational/AI-supported assessment
Hot-humid	High humidity, solar heat gain and limited nocturnal cooling	Cross-ventilation, shaded openings, wide eaves, ventilated roofs and screened openings	Simulate airflow, humidity conditions and comfort hours using locally representative weather data and verified occupancy assumptions.
Hot-dry	High daytime temperatures, intense solar exposure, dust and large diurnal temperature variation	Courtyards, shaded walls, controlled openings, reflective or insulated roofs, thermal-mass strategies and night ventilation where climatic conditions permit	Test solar exposure, envelope heat gain, night-purge potential and overheating hours under representative seasonal conditions.
Composite/transition	Seasonal variation in temperature, humidity and ventilation requirements	Adjustable openings, roof insulation, external shading, daylight control and flexible mixed-mode operation	Compare seasonal comfort, cooling demand, daylight-energy trade-offs and occupant-control scenarios.
Dense urban microclimate	Urban heat accumulation, reduced airflow and high surface heat storage	Tree canopy, permeable surfaces, shaded pedestrian environments, reduced heat-absorbing surfaces and protected ventilation corridors	Map heat exposure, canopy coverage, surface temperature, permeability and airflow pathways; apply AI-supported prediction only where sufficiently validated local datasets are available.

Source: Authors' synthesis based on bioclimatic and warm-climate evidence (Aflaki et al., 2015; Givoni, 1998; Koenigsberger et al., 1974; Li et al., 2018; Ochedi& Taki, 2022; Olgyay, 1963; Ziter et al., 2019).

Note: Table 2 is intended as a climate-screening guide rather than a nationally prescriptive design schedule. The suitability and magnitude of benefit of each strategy remain dependent on locally representative weather conditions, building geometry, envelope construction, occupancy, operational practices and neighbourhood characteristics. Computational simulation can support comparative assessment, whereas AI-based prediction or optimisation requires appropriate training data, validation and professional interpretation.

For Nigerian housing, passive responses should therefore vary with climatic conditions, urban density, occupancy behaviour, construction practice and practical constraints such as safety, dust, insects, noise and privacy. Computational solar, airflow and urban-heat analyses can be used to compare design alternatives. At the same time, AI-based prediction or optimisation may be added where suitable local datasets and validation procedures are available. Conventional simulation, CFD, GIS and parametric analysis should therefore be distinguished from AI-based methods rather than collectively described as AI-assisted analysis (Abdulkareem & Al-Maiyah, 2025; Adaji et al., 2019; Hong et al., 2017; Ochedi & Taki, 2022; UNEP, 2021; Wang, 2023).

At neighbourhood scale, cool roofs, green roofs, vegetation and tree canopy may modify heat exposure, but the magnitude and spatial distribution of their effects vary with surface properties, urban density, canopy coverage, imperviousness and local meteorology (Li et al., 2018; Norton et al., 2015; Ziter et al., 2019). Accordingly, neighbourhood-scale cooling measures should be evaluated alongside building-level passive strategies and local urban conditions rather than treated as uniformly applicable interventions.

Adaptive Comfort and Occupant-Centred Performance

Adaptive-comfort research consistently shows that occupants of naturally ventilated buildings may accept wider temperature ranges when they can adjust windows, fans, clothing, shading and activities (Brager & de Dear, 1998; Nicol & Humphreys, 2002). This adaptive capacity does not remove heat-health risk: WHO identifies high indoor temperature as a housing-related health concern, particularly for vulnerable populations (WHO, 2018). For naturally ventilated and mixed-mode housing, comfort assessment therefore requires both adaptive opportunity and explicit attention to overheating risk (ASHRAE, 2023; WHO, 2018).

Mixed-mode housing combines passive ventilation, air movement and intermittent mechanical cooling, so comfort outcomes depend on both environmental conditions and occupant control. Evidence on adaptive comfort and Nigerian residential conditions indicates that increased air movement, reduced radiant heat and usable controls can extend acceptable conditions, while reduced mechanical-cooling demand can lower household energy use and maintain some thermal protection during electricity interruptions (Adaji et al., 2019; de Dear & Brager, 2002; Hong et al., 2017; Nicol & Humphreys, 2002; UNEP, 2021).

Nigerian evidence is consistent in showing that local occupancy and measured thermal conditions are necessary for interpreting passive-housing performance. Abuja field studies document adaptation in low- and middle-income housing, while Nigerian design and simulation research links envelope and passive strategies with comfort and energy outcomes; more recent affordable-housing research reaches comparable conclusions for passive interventions (Abdulkareem & Al-Maiyah, 2025; Adaji et al., 2019; Ochedi & Taki, 2022). Accordingly, this review prioritises local measurement and post-occupancy evidence over direct transfer of comfort assumptions from dissimilar building and climate contexts.

Adaptive-comfort and heat-health literature identifies comfort hours, operative temperature, air movement, humidity, overheating exposure and occupant satisfaction as complementary indicators for naturally ventilated or mixed-mode housing assessment (ASHRAE, 2023; Brager & de Dear, 1998; Nicol & Humphreys, 2002; WHO, 2018). Used together, these indicators connect architectural decisions with thermal exposure, occupant adaptation and post-occupancy validation.

Table 3: Thermal comfort performance indicators for Nigerian housing

Indicator	What it measures	Design relevance	Data/AI input
Adaptive comfort hours	Occupied hours within acceptable comfort range	Tests naturally ventilated and mixed-mode housing performance	Climate data, occupancy profile and simulation output
Operative temperature (°C)	Combined effect of air temperature and radiant heat	Reveals roof, wall, glazing and shading performance	Thermal model and indoor sensor data
Air speed (m/s)	Cooling effect of natural breeze or fans	Supports comfort at higher indoor temperatures	CFD analysis, fan-use data and window-operation data
Relative humidity (%)	Moisture condition affecting heat stress	Critical for hot-humid Nigerian housing contexts	Weather data and humidity sensors
Overheating hours (h)	Occupied hours above a stated overheating or thermal-comfort criterion. Health-risk exceedance should be reported separately using an explicitly defined health-based threshold.	Indicates heat-risk exposure and passive survivability during power outages	Weather file, simulation and monitored indoor data
Occupant satisfaction	User perception of comfort and control	Validates model assumptions and post-occupancy performance	Post-occupancy surveys and AI-supported analytics

Source: Authors' synthesis based on adaptive-comfort, occupant-centred and heat-health evidence (Adaji et al., 2019; ASHRAE, 2023; Brager & de Dear, 1998; Li et al., 2021; Nicol & Humphreys, 2002; O'Brien et al., 2017; WHO, 2018).

Note. Adaptive-comfort compliance should be assessed only under the applicability conditions of the selected standard. Under ASHRAE Standard 55, the adaptive method applies to occupant-controlled naturally conditioned periods and should not be applied while mechanical cooling is operating. Relative humidity and health-risk exceedance are reported as complementary environmental indicators rather than as direct determinants of the ASHRAE adaptive-comfort limits.

Table 3 operationalises adaptive comfort through indicators that can be linked to design, simulation and post-occupancy evidence. AI-based comfort modelling remains sensitive to data quality, privacy requirements and transferability across climates and housing types; recommended alternatives therefore require professional interpretation against climatic appropriateness, spatial coherence, buildability, neighbourhood conditions and life-cycle affordability (Mulliner et al., 2013; OECD, 2024; UNESCO, 2021; Wei et al., 2018).

AI-Assisted Performance Analysis and Optimisation

AI- and data-driven methods can support building-energy prediction, thermal-comfort forecasting and intelligent control, whereas conventional building-performance simulation and simulation-based optimisation provide complementary means of comparing architectural design alternatives (Amasyali & El-Gohary, 2018; Attia et al., 2013; Merabet et al., 2021; Nguyen et al., 2014; Wang & Srinivasan, 2017; Wei et al., 2018). These approaches should not be treated as interchangeable. Machine-learning models derive predictive relationships from data and can support energy and comfort forecasting, although their accuracy depends on data quality, occupancy assumptions, model selection, training context and evaluation metrics (Amasyali & El-Gohary, 2018; Bourdeau et al., 2019; Wang & Srinivasan, 2017; Wei et al., 2018; Zhao & Magoulès, 2012). By contrast, simulation-based optimisation can systematically test orientation, envelope, glazing, shading, ventilation and mixed-mode alternatives under specified comfort, energy and cost constraints (Attia et al., 2013; Evins, 2013; Machairas et al., 2014; Nguyen et al., 2014).

Computational airflow and urban-scale analyses provide further complementary evidence. When natural ventilation is assessed using computational fluid dynamics (CFD) or related airflow models, credibility depends on appropriate geometry, boundary conditions, mesh quality, climatic inputs and validation (Chen, 2009; Hajdukiewicz et al., 2024; Omrani et al., 2017). Similarly, neighbourhood-scale analyses of cool roofs, green roofs, vegetation and tree canopy remain sensitive to surface properties, canopy coverage, urban morphology and local meteorology (Li et al., 2018; Ziter et al., 2019). GIS, building-energy simulation, CFD and urban-microclimate modelling should therefore be regarded as computational decision-support methods rather than AI in themselves; AI/ML may subsequently augment these methods through prediction, surrogate modelling, optimisation, pattern recognition or option ranking where appropriate and adequately validated data are available.

Across data-driven and simulation-based studies, model credibility depends substantially on the quality of inputs, explicit boundary conditions and assumptions, suitable evaluation metrics and independent validation (Amasyali & El-Gohary, 2018; Bourdeau et al., 2019; Coakley et al., 2014; Nguyen et al., 2014). In Nigerian applications, local calibration, sensitivity analysis, professional review and post-occupancy comparison should therefore accompany model-supported recommendations, particularly where climatic, construction and occupancy conditions differ from those represented in the original training or simulation context. For AI-supported decisions specifically, ISO/IEC 23894:2023 and UNESCO's AI ethics framework further emphasise risk management, transparency, accountability and human oversight (ISO, 2023; UNESCO, 2021).

Table 4: Operational computational and AI-assisted workflow for climate-responsive housing design

Stage	Inputs/tools	Output	Validation/safeguard
Pre-design	Local climate and weather data, GIS, site observations, urban-heat information and neighbourhood data	Climate and site-performance brief	Verify weather files, data provenance, site observations and climatic assumptions.
Concept design	Digital building geometry, solar and shading analysis, orientation studies and parametric option testing	Passive-design alternatives for professional evaluation	Architectural and planning review of climatic suitability, spatial quality, buildability and affordability
Performance testing	Conventional whole-building energy simulation, CFD where required, and urban-microclimate modelling	Comfort, overheating, airflow and cooling-load results	Sensitivity analysis, boundary-condition review, mesh-independence checks where applicable, and verification of modelling assumptions
AI-assisted prediction and optimisation	Validated ML models, simulation outputs, occupancy data, material properties and relevant environmental datasets	Energy and comfort forecasts, surrogate predictions or ranked design alternatives	Local calibration, independent error assessment, transparent performance metrics, transferability checks and professional interpretation
Professional decision review	Integrated architectural, planning, engineering, cost and performance evidence	Selected design option and documented performance justification	Multidisciplinary review of technical performance, affordability, constructability, climatic appropriateness and model uncertainty
Post-occupancy evaluation	Indoor and outdoor monitoring, occupant surveys, operational records and energy-use data	Measured performance feedback and evidence of prediction–performance differences	Compare predicted and measured outcomes; recalibrate models and revise design assumptions where necessary.
Feedback and learning	Validated POE findings, updated datasets and documented implementation experience.	Updated design criteria, model assumptions and planning guidance	Maintain transparent records of model updates, data limitations, professional decisions and lessons for subsequent projects

Source: Authors' synthesis based on building-energy prediction, optimisation, calibration, validation and responsible-AI guidance (Amasyali & El-Gohary, 2018; Attia et al., 2013; Bourdeau et al., 2019; Coakley et al., 2014; Evins, 2013; ISO, 2023; Nguyen et al., 2014; OECD, 2024; UNESCO, 2021).

Note: Building-energy simulation, CFD, GIS and urban-microclimate modelling are treated here as computational performance-analysis methods rather than AI in themselves. AI/ML methods may augment these processes through prediction, surrogate modelling, optimisation and option ranking where suitable validated datasets exist. EnergyPlus, DesignBuilder and related simulation environments are represented in building-performance optimisation literature, while CFD and neighbourhood microclimate models support airflow and urban-heat analysis. In each case, model credibility remains dependent on appropriate boundary conditions, transparent assumptions, sensitivity testing and validation (Attia et al., 2013; Chen, 2009; Evins, 2013; Hajdukiewicz et al., 2024; Nguyen et al., 2014).

Architectural Decision-Making and Professional Accountability

Post-occupancy evaluation and performance-in-use research support a feedback model in which measured outcomes and occupant experience inform subsequent architectural and planning decisions rather than treating project completion as the end of performance assessment (Bordass & Leaman, 2005; Leaman & Bordass, 2007; Zimmerman & Martin, 2001). Within the proposed framework, architectural practice integrates climate, form, space, materiality, envelope performance and occupant needs. At the same time, urban and regional planning relates housing performance to settlement form, infrastructure, green space, density, development control and neighbourhood heat. Life-cycle affordability remains an important cross-cutting constraint because capital cost, operating expenditure, maintenance requirements and household access affect whether passive and technology-supported measures remain feasible for intended users (Mulliner et al., 2013).

The term architecture-led should therefore not be interpreted as an architect-only process. Within the proposed conceptual framework, architects coordinate climatic performance with spatial, functional, material and aesthetic decisions, while urban and regional planners, building-performance specialists, relevant engineers, cost professionals and data/AI specialists contribute according to project requirements. AI- or simulation-generated outputs should inform rather than replace competent professional judgement, with model assumptions, limitations, interpretation and decision accountability explicitly documented throughout the workflow (ISO, 2023; OECD, 2024; UNESCO, 2021).

Table 5: Professional deliverables in a computationally and AI-augmented housing workflow

Professional / team	Core responsibility	Key deliverable	Computational/AI-supported evidence
Architect	Integrates climate, orientation, form, space, envelope, materials, comfort and architectural quality	Climate-responsive architectural brief, passive-design alternatives and integrated design decisions	Solar exposure, shading performance, adaptive-comfort compliance, overheating, airflow and cooling-load results
Urban and Regional Planner	Relates housing design to neighbourhood form, development control, infrastructure, liveability and urban heat	Climate-responsive layout and development-control recommendations	Urban-heat maps, tree-canopy coverage, ventilation corridors, surface permeability, density and neighbourhood scenarios
Building-performance / energy specialist	Develops and evaluates whole-building performance models and establishes credible performance assumptions	Documented simulation model, calibration report and uncertainty/sensitivity assessment	Energy use, cooling load, indoor temperature, comfort compliance, overheating and calibrated model outputs
Engineer / CFD specialist	Evaluates natural ventilation, airflow, mechanical systems and relevant environmental-performance conditions	Airflow and ventilation assessment with documented modelling assumptions	CFD results, air-speed distributions, pressure fields, ventilation effectiveness and mesh/boundary-condition checks
Cost professional	Evaluates capital, maintenance, operational and life-cycle affordability implications of design alternatives	Comparative capital and life-cycle cost assessment	Cost implications of passive options, cooling-energy expenditure, maintenance requirements and affordability scenarios
Data / AI specialist	Develops, trains, validates and documents AI/ML models and associated data-governance procedures	Validated predictive or optimisation model with transparent documentation	Training and validation metrics, error measures, uncertainty, explainability, transferability checks and data-governance records
Joint multidisciplinary team	Integrates architectural, planning, engineering, performance, cost, AI and implementation considerations	Documented performance package for professional and regulatory design review	Transparent assumptions, applicable standards, simulations and AI outputs, sensitivity analysis, uncertainty assessment and professional review record
Post-occupancy evaluation team	Compares predicted performance with measured conditions and occupant experience	POE report and recommendations for model/design refinement	Sensor data, occupant feedback, energy records, prediction–measurement comparison and calibrated model updates

Source: Authors' synthesis based on post-occupancy evaluation, occupant-centred performance, planning integration, building-performance validation and responsible-AI governance (Bordass & Leaman, 2005; Coakley et al., 2014; ISO, 2023; Leaman & Bordass, 2007; Li et al., 2021; Norton et al., 2015; O'Brien et al., 2017; OECD, 2024; UNESCO, 2021).

Note: Professional assignments should be adapted to project scale, procurement arrangements, applicable statutory responsibilities and available expertise. The framework does not treat AI systems as accountable professional actors; computational and AI-generated outputs remain decision-support evidence subject to competent human interpretation, transparent documentation and professional accountability (ISO, 2023; OECD, 2024; UNESCO, 2021).

Framework for AI-Augmented Passive Housing Design

The proposed framework organises the reviewed evidence into a pre-design, design, testing, planning-review, approval and post-occupancy sequence. Climate information informs passive architectural design; AI-assisted analysis compares alternatives; planning review addresses neighbourhood form, infrastructure and development-control conditions; and post-occupancy evidence updates subsequent assumptions. The performance indicators reflect established comfort, overheating, occupant-centred performance, neighbourhood heat and affordability evidence (ASHRAE, 2023; Li et al., 2021; Mulliner et al., 2013; O'Brien et al., 2017; WHO, 2018).

Table 6: Implementation framework and KPIs for Nigerian cities

Component	**Implementation focus**	**Key performance indicator**	**Professional lead**
Climate intelligence	Site heat, wind, rainfall, flood exposure and climate-risk mapping	Documented heat, wind, rainfall and flood-risk assessment	Urban and Regional Planner / Architect
Passive-first design	Orientation, roof, envelope, shading and natural ventilation	Comfort hours (%) and cooling-load reduction (%)	Architect
AI option testing	Compare layouts, materials, glazing, vegetation and mixed-mode scenarios	Ranked alternatives with sensitivity-analysis record	Architect
Design affordability and life-cycle review	Capital cost, cooling expenditure, maintenance and passive-design affordability	Documented life-cycle cost and affordability assessment	Architect / Urban & Regional Planner
Neighbourhood liveability	Shade, airflow, drainage, access and green infrastructure	Tree-canopy coverage (%) and permeable surface ratio (%)	Urban & Regional Planner
Approval and delivery	Performance documentation, code alignment and procurement decisions	Approval-ready performance package completed	Architecture-planning team
Feedback governance	Sensors, POE, satisfaction and policy learning	Post-occupancy satisfaction score and calibrated model update	Architecture-planning team

Source: Authors' synthesis based on climate, adaptive-comfort, building-performance, AI/optimisation, urban-heat and affordability evidence (Amasyali & El-Gohary, 2018; ASHRAE, 2023; Li et al., 2021; Mulliner et al., 2013; NiMet, 2026; Nguyen et al., 2014; Norton et al., 2015; O'Brien et al., 2017; Perini & Magliocco, 2014; UNESCO, 2021).

Measurable performance indicators connect the proposed framework with the reviewed evidence. Occupant-centred indicators link architectural design and operation to comfort and measured performance, while vegetation, urban density and green infrastructure influence local temperature and cooling conditions at neighbourhood scale (Li et al., 2021; Norton et al., 2015; O'Brien et al., 2017; Perini & Magliocco, 2014). Housing affordability and lifecycle cost add a further performance dimension by testing whether thermal-resilience measures remain feasible for intended households (Mulliner et al., 2013).

Discussion

The synthesis does not identify a universally superior passive or computational strategy for thermally resilient housing. Rather, it indicates that effective performance depends on the interaction of climatic conditions, architectural decisions, occupant behaviour, neighbourhood context and the quality of analytical evidence used to support design choices. Within this relationship, AI is more appropriately positioned as decision support than as an autonomous design authority: passive design establishes the physical and spatial alternatives, adaptive-comfort evidence provides occupant-centred performance criteria, simulation evaluates design consequences, and data-driven methods can assist prediction, optimisation and option ranking (Amasyali & El-Gohary, 2018; Ochedi & Taki, 2022; UNESCO, 2021). Planning considerations extend these decisions beyond individual dwellings by incorporating urban heat, vegetation, density, infrastructure and neighbourhood airflow (Norton et al., 2015; Ochedi & Taki, 2022). The value of AI therefore lies in supporting comparison among contextually appropriate alternatives rather than generating design prescriptions independently of architectural and planning judgement.

The reviewed evidence also reveals important trade-offs among passive-design strategies. Increased natural ventilation may improve heat dissipation and extend acceptable indoor conditions, but its practical effectiveness may be constrained by noise, dust, insects, privacy and security concerns in occupied housing (Hong et al., 2017; Ochedi & Taki, 2022; UNEP, 2021). Increased shading can reduce solar heat gain but may also affect daylight availability and façade performance, requiring coordinated rather than isolated optimisation of thermal and visual objectives (Harkouss et al., 2018; Hu et al., 2023). Similarly, thermal mass is not inherently beneficial in every warm climate; its effectiveness depends on diurnal temperature variation, ventilation and the capacity to release stored heat during cooler periods (Givoni, 1998; Hyde, 2000). These interactions reinforce the need for climate- and household-specific multi-objective design rather than universal passive prescriptions.

Comparable tensions arise in model-supported decision-making. Data scarcity, uncertain boundary conditions and simplified occupancy assumptions can produce apparently precise outputs that exceed the certainty of the underlying evidence, while higher initial costs or technically demanding interventions may constrain adoption despite predicted performance benefits (Bourdeau et al., 2019; Mulliner et al., 2013; Yan et al., 2015). Building-performance research further demonstrates that predicted and measured outcomes may diverge where construction quality, weather data, occupant behaviour and actual operation differ from model assumptions (Coakley et al., 2014; de Wilde, 2014). AI-supported optimisation may therefore improve the speed and breadth of option screening, but it can simultaneously increase dependence on representative datasets, computational expertise, transparent model evaluation and professional interpretation.

Transferability consequently emerges as a central limitation across passive-design, thermal-comfort, simulation and AI literature. Models developed from dissimilar climates, construction systems, occupancy patterns or mechanically conditioned buildings may perform poorly when transferred to naturally ventilated or mixed-mode Nigerian dwellings (Amasyali & El-Gohary, 2018; Bourdeau et al., 2019; Hong et al., 2017). The appropriate response is not to reject international evidence, but to distinguish methodological transferability from direct performance transfer. International studies can inform analytical methods, candidate passive strategies and model-development procedures. In contrast, final Nigerian design recommendations should remain conditional on local climatic data, construction practice, occupancy behaviour, affordability and empirical validation. Responsible implementation therefore requires a locally calibrated and professionally reviewed workflow rather than direct adoption of externally generated model outputs (UNESCO, 2021).

Evidence Boundaries and Transferability

Across the heterogeneous literature reviewed, the evidence generally suggests three recurring patterns: early integration of passive measures can reduce unwanted heat gains and mechanical-cooling demand; adaptive opportunity and locally relevant weather conditions improve interpretation of naturally ventilated housing; and AI-supported or simulation-ranked alternatives require validation and professional judgement before implementation (Brager & de Dear, 1998; Givoni, 1998; Nicol & Humphreys, 2002; Ochedi & Taki, 2022; Wei et al., 2018). Because this review does not calculate pooled effect sizes, these conclusions should be interpreted as recurring evidence patterns rather than quantified comparative effects. The magnitude of benefit associated with particular strategies remains dependent on climate, building form, envelope characteristics, occupancy, operating mode and neighbourhood conditions.

The evidence also differentiates the applicability and limitations of the principal analytical methods. PMV/PPD provides standardised prediction under defined environmental and personal variables, whereas adaptive approaches are better suited to contexts in which occupants have meaningful opportunities to interact with and adjust to their environment; both require compliance with their respective applicability conditions (ASHRAE, 2023; Fanger, 1970; ISO, 2025; Nicol & Humphreys, 2002). Simulation-based optimisation provides physically interpretable comparison of design alternatives but remains sensitive to modelling assumptions, boundary conditions and calibration. Machine-learning methods can efficiently identify patterns and generate predictions from large datasets, yet their performance may deteriorate when the training data differ substantially from the target climatic, building or occupancy context (Amasyali & El-Gohary, 2018; Bourdeau et al., 2019; Nguyen et al., 2014). Method selection should therefore follow the building operating mode, available data, stage of design and intended decision rather than a presumed superiority of AI over conventional simulation.

Within the reviewed corpus, international evidence provides substantially greater methodological breadth, including passive-design optimisation, AI prediction, simulation calibration, airflow modelling and occupant-behaviour analysis, whereas the smaller Nigerian evidence base provides greater contextual relevance to local climate, occupancy and construction conditions (Adaji et al., 2019; Ochedi& Taki, 2022). This asymmetry places an important boundary on the synthesis. International findings are most defensible when used to identify candidate strategies, analytical procedures and hypotheses for local testing rather than as direct evidence of Nigerian performance. Accordingly, Nigerian design recommendations should be conditional on representative climatic data, local construction systems, household operation, affordability constraints and measured performance evidence. The combined literature therefore supports explicit reporting of transferability limits and context-sensitive method selection rather than universal preference for either AI or conventional simulation, or for either adaptive or PMV-based thermal-comfort assessment.

Practice and Policy Implications

The reviewed evidence supports piloting the incorporation of passive-performance targets, climate-specific guidance, post-occupancy evaluation and responsible-AI requirements into housing briefs and development-control processes, with local evaluation before wider institutional adoption. For publicly supported housing, verified weather data, explicitly stated comfort criteria, life-cycle affordability assessment and documented professional review can provide a transparent and reviewable basis for comparing AI-assisted or simulation-ranked design alternatives (ASHRAE, 2023; Bordass & Leaman, 2005; Mulliner et al., 2013; OECD, 2024; UNESCO, 2021). Such requirements should complement, rather than replace, professional judgement and should be adapted to local climatic conditions, housing typologies, household affordability and available technical capacity.

Table 7 translates recurring evidence on passive design, planning integration, post-occupancy evaluation, affordability and responsible-AI governance into implementation-level actions that may be piloted and evaluated within Nigerian housing delivery and development-control processes (Bordass & Leaman, 2005; Mulliner et al., 2013; Norton et al., 2015; Ochedi & Taki, 2022; OECD, 2024; UNESCO, 2021).

Table 7: Implementation-level recommendations for AI-augmented climate-responsive housing

Implementation level	Recommendation
Project level	**Architectural design brief:** Define passive-design strategies, applicable thermal-comfort criteria, shading and ventilation measures, and comparative cooling-load performance before construction documentation.
Planning-authority level	**Development-control criteria:** Incorporate consideration of urban heat exposure, ventilation corridors, tree canopy, surface permeability, drainage and neighbourhood-scale cooling conditions into planning appraisal.
Professional-education level	**Professional development:** Strengthen capacity in building-performance simulation, AI-assisted analysis, adaptive thermal comfort, post-occupancy evaluation and responsible AI for Nigerian housing applications.
Public-housing-agency level	**Public-housing procurement brief:** Specify passive-performance targets, life-cycle cost and affordability considerations, maintenance requirements and post-occupancy monitoring provisions.
Cross-disciplinary project-appraisal level	**Design and planning appraisal:** Evaluate life-cycle energy cost, passive-cooling benefits, maintenance implications, neighbourhood access, affordability and relevant climate-risk exposure through coordinated professional review.
Research and data-governance level	**AI-governance requirements:** Require transparent assumptions, appropriate local calibration, data-privacy protection, explainability where applicable and documented professional oversight of AI-supported decisions.

Source: Authors' synthesis based on passive-design, thermal-comfort, post-occupancy, affordability, urban-heat and responsible-AI evidence (ASHRAE, 2023; Bordass & Leaman, 2005; ISO, 2023; Mulliner et al., 2013; Norton et al., 2015; Ochedi & Taki, 2022; OECD, 2024; UNESCO, 2021).

Limitations and Future Research

This review is limited by its structured narrative rather than systematic design, purposive and iterative source selection, predominant dependence on published English-language evidence, and the limited reproducibility of searches conducted through broad discovery and publisher platforms. It does not provide a pooled estimate of passive-design effectiveness or a formal risk-of-bias score. At the same time, substantial heterogeneity exists across climatic contexts, building types, occupancy conditions, analytical methods and performance indicators. The relatively small and geographically uneven Nigerian measured evidence base further restricts direct comparison across hot-humid, hot-dry and composite climatic contexts and limits national generalisation. Rapid changes in AI software, proprietary algorithms and data availability may also shorten the relevance of particular technical applications. Furthermore, the proposed framework remains conceptual and has not yet been empirically validated through completed and occupied Nigerian housing projects.

Future research should prioritise the development of open and geographically diverse Nigerian thermal-performance datasets that combine monitored indoor and outdoor environmental conditions with occupant responses and operating behaviour. Comparative studies should evaluate AI predictions against calibrated building-performance simulation and, where appropriate, validated CFD and field-monitoring evidence. Further work should test climate-specific passive-housing alternatives across representative Nigerian climatic contexts and evaluate their thermal performance, energy implications, life-cycle cost, affordability, constructability and post-occupancy outcomes. Research should also develop governance protocols addressing data privacy, model explainability, professional accountability and community participation. More advanced applications, including digital twins for post-occupancy performance and maintenance, should be investigated after sufficiently robust local datasets and validated baseline models have been established. Longitudinal studies are also required to determine whether predicted comfort, energy and affordability benefits persist during actual occupation.

Conclusion

The reviewed evidence supports a proposed AI-augmented, climate-responsive housing workflow in which passive architectural design and adaptive thermal comfort provide the primary physical and occupant-centred criteria. In contrast, conventional building-performance simulation and appropriately validated AI methods support comparison, prediction and optimisation. Credible application depends on verified local weather data, explicit occupancy and operating assumptions, appropriate comfort models, sensitivity analysis, transparent model assumptions, professional review and post-occupancy validation, particularly because Nigerian measured residential datasets remain geographically and methodologically limited.

The article contributes a proposed architecture-led conceptual workflow linking climate intelligence, passive design, conventional performance simulation, AI-assisted comparison, planning integration and performance-in-use feedback. The framework should therefore be regarded as a testable synthesis of the reviewed evidence rather than an empirically validated Nigerian design standard. Future empirical validation should combine monitored indoor and outdoor thermal conditions, occupant responses and operating behaviour, energy-use data, calibrated performance models and implementation-cost evidence across representative Nigerian climatic contexts. Such validation is necessary before the framework's performance indicators, AI-supported procedures or passive-design recommendations are generalised nationally. The principal contribution of the review is consequently to provide a structured basis for integrating architectural design, occupant-centred thermal performance, computational analysis, planning considerations and responsible professional oversight in the future development and testing of thermally resilient housing in Nigeria.

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Table S1. Search strategy and evidence-source framework for the structured narrative review

Search domain	Recommended reproducible search expression*	Primary search sources	Purpose/evidence sought	Eligibility emphasis
S1. Passive architectural design and thermal comfort	("passive design" OR "passive cooling" OR "climate-responsive housing") AND ("adaptive thermal comfort" OR "thermal comfort") AND ("Nigerian housing" OR Nigeria)	Scopus; Google Scholar; supplementary searches in ScienceDirect, Taylor & Francis Online and MDPI-hosted journals	Identify evidence relating architectural form, envelope, shading, ventilation, materials and passive cooling to indoor thermal conditions and occupant comfort.	Residential studies and transferable warm-climate evidence; emphasis on passive-design variables, comfort indicators and occupant adaptation.
S2. AI and building-performance prediction	("AI in building design" OR "artificial intelligence" OR "machine learning") AND ("building energy" OR "thermal comfort" OR "building performance") AND (prediction OR analytics)	Scopus; Google Scholar; ScienceDirect; Taylor & Francis Online; MDPI-hosted journals	Identify applications of AI/data-driven methods to building-energy prediction, comfort prediction and performance analytics.	Peer-reviewed analytical and methodological studies with explicit building-performance applications and identifiable validation procedures.
S3. Simulation-based design optimisation	("building-performance optimisation" OR "simulation-based optimisation") AND ("passive design" OR "climate-responsive housing" OR "building performance")	Scopus; Google Scholar; ScienceDirect; Taylor & Francis Online	Identify studies using simulation or optimisation to compare orientation, envelope, glazing, shading, ventilation and related design alternatives.	Studies reporting design variables, model assumptions, performance outputs and, where available, sensitivity or validation procedures.
S4. Natural ventilation and airflow modelling	("natural ventilation" OR airflow) AND (CFD OR simulation OR modelling) AND ("building performance" OR housing)	Scopus; Google Scholar; ScienceDirect; Taylor & Francis Online	Identify evidence on ventilation effectiveness, airflow modelling and the methodological requirements for credible CFD or related airflow analysis.	Building-scale or transferable warm-climate studies with explicit treatment of boundary conditions, geometry, mesh/model quality or validation.
S5. Urban cooling and neighbourhood-scale performance	("urban cooling" OR "urban heat") AND ("passive cooling" OR vegetation OR "climate-responsive housing")	Scopus; Google Scholar; ScienceDirect; relevant institutional repositories	Identify evidence linking vegetation, tree canopy, roofs, surfaces, urban form and neighbourhood configuration with heat exposure.	Urban-climate and planning studies relevant to housing layout, neighbourhood cooling and development-control decisions.
S6. Occupant behaviour and post-occupancy performance	("post-occupancy evaluation" OR "occupant behaviour" OR "occupant-centered performance") AND ("thermal comfort" OR "building performance" OR housing)	Scopus; Google Scholar; ScienceDirect; Taylor & Francis Online	Identify evidence on occupant adaptation, control, monitoring, performance gaps and feedback from occupied buildings.	Studies addressing occupant behaviour, comfort responses, performance-in-use, measured conditions or post-occupancy evaluation.

S7. Nigerian housing and climatic context	(“Nigerian housing” OR Nigeria) AND (“passive design” OR “thermal comfort” OR “climate-responsive housing” OR “building energy”)	Scopus; Google Scholar; Nigerian/institutional repositories	Identify directly contextual Nigerian evidence against which internationally derived findings can be interpreted.	Priority to Nigerian residential field studies, simulation/design studies, climate evidence and building-energy guidance.
S8. Responsible AI and governance	(“ethical AI” OR “responsible AI” OR “AI governance”) AND (“building design” OR “building performance” OR planning)	Scopus; Google Scholar; institutional sources	Identify governance requirements for transparency, risk management, privacy, accountability and professional oversight in AI-supported decisions.	Scholarly evidence and authoritative standards/guidance with relevance to professional built-environment decision-making.
S9. Standards, policy and institutional guidance	Targeted searches using document title, institution and thematic terms including adaptive thermal comfort, building energy efficiency, sustainable cooling, housing health, climate action and AI risk management	ASHRAE; ISO; IEA; UNEP &GlobalABC; UN-Habitat; WHO; World Bank; UNESCO; OECD; NiMet and relevant Nigerian government sources	Provide normative definitions, applicability conditions, policy context, national climate information and responsible-AI guidance.	Authoritative standards, policy documents and institutional reports; treated separately from peer-reviewed analytical evidence.