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Artificial Intelligence-Assisted Green Building Technologies for Urban Regeneration: A Design Support Framework for Low-Carbon, Climate-Adaptive Neighborhoods

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Abstract

Rapid urbanization and escalating climate change pressures have intensified the need for systematic, evidence-based approaches to urban regeneration, as existing built environments contribute approximately 40% of global energy consumption and 36% of CO_2 emissions. Existing research on the application of artificial intelligence (AI) to the integrated selection of green building technology packages at the neighborhood scale remains limited, with conventional design workflows lacking the computational capacity to evaluate the vast combinatorial solution space of technology interactions, and with current frameworks rarely integrating thermal comfort, climate adaptation, and explainability within a unified multi-objective structure. This study aims to develop and validate a comprehensive AI-assisted design support framework enabling rapid, transparent, and evidence-based selection of optimal green building technology packages for low-carbon, climate-adaptive urban regeneration. To address this, a multi-scale framework was employed that couples city-level climate scenario modelling (RCP 4.5/8.5), neighbourhood-level microclimate simulation (CFD/ENVI-met), and building-level energy analysis (EnergyPlus/IES-VE) through an AI core engine comprising machine learning surrogate models (ANN, Random Forest, XGBoost), NSGA-II/III multi-objective evolutionary optimisation, urban morphology clustering, and SHAP-based explainable AI, trained and validated on a synthesis of 241 peer-reviewed studies (2022-2025). The results indicate that AI-optimized technology packages achieve 22% - 30% cooling energy reductions versus 6.5% - 20% for individual interventions, outdoor thermal comfort improvements of 2.0˚C - 3.5˚C (UTCI), carbon payback periods of 4 - 7 years, and a 19-percentage-point climate-resilience advantage over conventional retrofits under RCP 8.5 (2050), while reducing design itera-

tion time from weeks to hours (surrogate $R^2 > 0.92$). These findings suggest that AI-assisted, multi-scale, explainable optimization provides a scalable, transferable, and stakeholder-transparent pathway for accelerating low-carbon, climate-adaptive urban regeneration from individual buildings to district-scale projects of 500 - 2000 buildings.

Keywords

Artificial Intelligence, Green Building Technologies, Urban Regeneration, Machine Learning, Climate Adaptation, Multi-Objective Optimization

1. Introduction

The built environment stands at the intersection of two defining global challenges: accelerating urbanization and worsening climate change. Urban areas currently account for approximately 75% of global primary energy consumption and generate roughly 70% of greenhouse gas emissions, with buildings and construction responsible for approximately 34% of global energy demand and 37% of energy- and process-related CO_2 emissions worldwide (UNEP & GlobalABC, 2024). Projections from the United Nations indicate that 68% of the global population will reside in urban areas by 2050, placing unprecedented demands on urban infrastructure and built environment governance (UN DESA, 2022). Against this backdrop, urban regeneration, the systematic transformation of existing built environments, presents both the greatest challenge and the most significant opportunity for achieving meaningful reductions in energy consumption, carbon emissions, and climate vulnerability at scale.

The complexity of urban regeneration decision-making is substantial. A typical neighbourhood-scale regeneration project may involve hundreds to thousands of buildings spanning diverse typologies, construction eras, ownership structures, and microclimatic exposures. Each building presents a unique combination of retrofit opportunities across passive design interventions, active system upgrades, renewable energy integration, and nature-based solutions. The number of possible technology combinations grows combinatorially with building count, rendering exhaustive manual evaluation computationally and economically infeasible (Shan et al., 2025). Traditional design workflows relying on expert judgment, simplified rules of thumb, and limited parametric studies are systematically unable to explore this solution space, frequently missing non-intuitive technology combinations that deliver superior performance through synergistic interactions (Cong et al., 2024).

Artificial intelligence has emerged as a transformative enabler for addressing this complexity. Machine learning surrogate models can replace computationally expensive physics-based simulations with near-instantaneous performance predictions, enabling exploration of millions of design alternatives within practical timeframes (Bibri et al., 2025). Multi-objective evolutionary algorithms such as

NSGA-II and NSGA-III systematically navigate trade-offs between energy savings, capital costs, lifecycle carbon emissions, and thermal comfort, generating Pareto-optimal solution sets that present decision-makers with a transparent portfolio of high-performing alternatives (Elshafei et al., 2022). Explainable AI techniques, particularly SHAP (SHapley Additive exPlanations) value analysis, transform opaque model predictions into interpretable design insights that align with domain expertise and build stakeholder confidence (Chen et al., 2025). Data-driven clustering methods enable rapid identification of building archetypes and urban morphology patterns, supporting scalable prioritisation of retrofit interventions across heterogeneous urban districts (Ge et al., 2024).

Digital twin technologies further extend AI capabilities by enabling real-time monitoring, predictive maintenance, and adaptive management of building performance over time (Soni et al., 2025). The integration of IoT sensor networks with ML-based control optimization has demonstrated additional energy savings of 10-15% beyond static design optimization, creating a continuous improvement cycle that enhances long-term resilience (Yang, 2025). Generative AI models offer emerging potential for automated design alternative generation, while physics-informed neural networks that embed thermodynamic constraints may improve prediction accuracy and reduce training data requirements (Yao et al., 2025). Graph neural networks show promise for modelling spatial relationships within urban districts, potentially improving district-scale optimization and technology coordination (Xu et al., 2026).

Despite these advances, significant research gaps constrain practical adoption. Current AI-driven frameworks predominantly focus on single-objective energy optimization, inadequately integrating thermal comfort, climate adaptation, embodied carbon, and nature-based solutions within unified multi-objective frameworks (Bibri et al., 2024). Model transferability across climatic zones, building typologies, and regulatory contexts remains underexplored, limiting generalizability of findings (Feng et al., 2024). The performance gap between predicted and actual post-occupancy energy consumption, often reaching 20% - 40% due to occupant behavior, construction quality variations, and operational deviations from design assumptions, is inadequately addressed in existing frameworks (Gaspari et al., 2017). Furthermore, the integration of AI-assisted tools with participatory design processes, interdisciplinary collaboration, and policy implementation pathways requires substantially greater development (Sanchez, 2023).

Climate change adaptation introduces additional complexity that conventional design practice systematically neglects. Technology packages optimized for current climate conditions may experience significant performance degradation under future climate scenarios, with cooling degree days projected to increase by 30-50% under RCP 8.5 by 2050 (IPCC, 2023). Urban regeneration investments with 30 - 50-year design lifespans will inevitably operate under substantially different climatic conditions from those prevailing at design time, necessitating forward-looking, climate-adaptive design strategies that maintain effectiveness across pro-

jected climate trajectories (Lützkendorf & Balouktsi, 2022).

This paper addresses these gaps by presenting a comprehensive, multi-scale AI-assisted design support framework for low-carbon, climate-adaptive urban regeneration. The framework synthesizes advances in AI-driven building energy optimization, digital twin technologies, climate-responsive design simulation, and nature-based solutions within a unified, scalable architecture. The specific contributions of this paper are 1) a systematic review of state-of-the-art AI methods for green building design and urban regeneration (2022-2025); 2) a novel multi-scale framework architecture integrating city-level climate scenarios, neighborhood-level microclimate modelling, and building-level energy simulation with an AI core engine; 3) a comprehensive synthesis of performance evidence from recent implementations across diverse urban contexts and climatic zones; 4) explainability analysis revealing key performance drivers and context-specific design guidelines; and 5) a critical assessment of limitations and future research directions for advancing AI-assisted sustainable urban design; and 6) a reproducible systematic review protocol and a source-trail table ensuring full transparency of the provenance of all reported results.

The remainder of this paper is organized as follows. Section 2 presents the theoretical foundations, framework architecture, and detailed methodology. Section 3 synthesises results from recent applications and case studies, including performance benchmarking, technology synergy analysis, morphology sensitivity, climate scenario assessment, and scalability evidence. Section 4 discusses implications for practice, policy, and research, addressing limitations and future directions. Section 5 concludes with key recommendations for researchers, practitioners, and policymakers.

2. Materials and Methods

2.1. Theoretical Foundations and Framework Design Philosophy

The proposed AI-assisted design support framework is grounded in three theoretical pillars: systems thinking applied to urban energy metabolism, multi-criteria decision analysis (MCDA) for complex trade-off navigation, and computational intelligence for high-dimensional optimization. Urban energy metabolism theory conceptualizes the city as a complex adaptive system in which energy flows, material cycles, and information processes interact across multiple scales (Kennedy et al., 2007). This systemic perspective motivates the framework's hierarchical multi-scale architecture, which captures cross-scale interactions between urban form, microclimate conditions, and building energy systems that single-scale analyses inevitably miss (Reinhart & Cerezo Davila, 2016).

The framework's design philosophy is governed by four core principles. First, scalability: the framework must be applicable across diverse urban contexts, building typologies, and climatic zones without requiring complete recalibration for each new application. This is achieved through data-driven clustering that identifies transferable building archetypes and through transfer learning approaches

that adapt pre-trained models to new contexts with limited additional data (Pan & Yang, 2010). Second, transparency: all AI-generated recommendations must be accompanied by interpretable explanations that enable practitioners and stakeholders to understand, verify, and contextualize findings. This principle drives the integration of SHAP-based explainability throughout the framework (Lundberg & Lee, 2017). Third, integration: the framework must synthesize multiple AI methods, simulation tools, and data sources within a unified digital toolchain that supports seamless workflow from data collection to decision output. Fourth, adaptability: the framework must support iterative refinement, real-time operational monitoring, and future climate scenario analysis, enabling continuous improvement over the full lifecycle of regenerated urban districts (Taddeo & Floridi, 2018).

2.2. Multi-Scale Framework Architecture

As illustrated in Figure 1, the framework operates across three interconnected spatial scales, each contributing distinct information to the overall design support process. At the city scale, climate change scenario modelling generates future weather files under IPCC RCP 4.5 and RCP 8.5 pathways for 2030-, 2050-, and 2080-time horizons, using tools such as CCWeatherGen and Meteonorm (Jentsch et al., 2013). Urban heat island (UHI) analysis quantifies the thermal amplification effects of urban density, impervious surfaces, and anthropogenic heat emissions, providing spatially resolved boundary conditions for neighborhood-scale simulations (Oke et al., 2017). City-level carbon emission inventories establish baseline emission profiles and target trajectories aligned with national and municipal climate commitments.

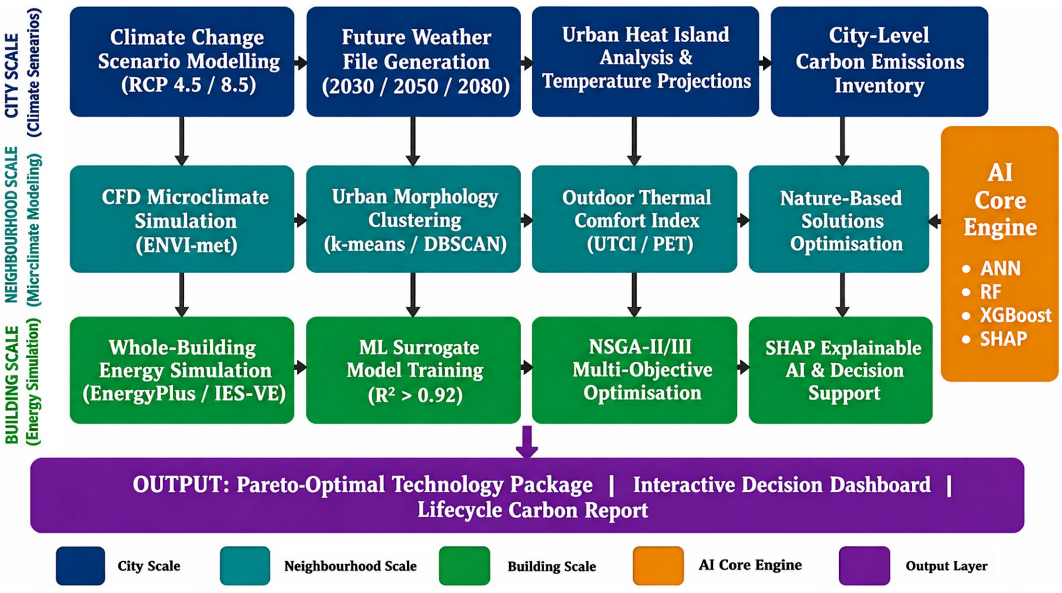


Figure 1. AI-assisted multi-scale design support framework architecture for urban regeneration. The framework integrates three spatial scales (city, neighborhood, and building) with an AI core engine comprising ANN, Random Forest, XGBoost, and SHAP-based explainability, producing Pareto-optimal technology packages and interactive decision dashboards.

At the neighborhood scale, computational fluid dynamics (CFD) and ENVI-met microclimate simulations model outdoor thermal conditions, wind patterns, and surface temperatures at 1 - 5 meter spatial resolution (Bruse & Fleer, 1998). These simulations predict Universal Thermal Climate Index (UTCI) and Physiological Equivalent Temperature (PET) distributions across outdoor spaces, informing the placement and sizing of nature-based solutions. Urban morphology clustering algorithms segment heterogeneous building stocks into homogeneous typological groups based on geometric, thermal, and operational characteristics, enabling targeted technology recommendations for each morphology type (Deng et al., 2022). At the building scale, whole-building energy simulation tools, principally EnergyPlus, DesignBuilder, and IES-VE, generate high-fidelity performance predictions for individual building archetypes under diverse technology configurations and boundary conditions (Crawley et al., 2001). These simulation results form the training datasets for ML surrogate models, which subsequently enable near-instantaneous performance predictions across the full technology solution space. The three scales are coupled through a data exchange layer that propagates climate boundary conditions downward (city-neighborhood-building) and aggregates performance results upward (building-neighborhood-city), capturing cross-scale feedback mechanisms that single-scale analyses miss (Allegrini et al., 2015).

Boundary Condition Exchange between Spatial Scales

Cross-scale coupling is implemented through a structured data exchange layer that harmonizes boundary conditions across the three modelling domains at an hourly temporal resolution, consistent with established practice in urban building energy modelling (Reinhart & Cerezo Davila, 2016; Allegrini et al., 2015) and with the computational timestep of both the microclimate and building energy models. Downward coupling from the city to the neighborhood scale is achieved by perturbing observed meteorological records, namely air temperature, relative humidity, wind velocity and direction, and global solar radiation, with the RCP specific warming signal (IPCC, 2023) and spatially resolved urban heat island increments of 2˚C - 5˚C (Oke et al., 2017), which are then prescribed as forcing files for the ENVI-met and OpenFOAM microclimate simulations (Bruse & Fleer, 1998). In the subsequent transfer from the neighborhood to the building scale, the microclimate model outputs hourly air temperature at the surface layer, longwave radiation fluxes, and wind pressure coefficients at each building facade, which are encoded as modified weather and boundary condition files for the EnergyPlus and IES VE building energy models (Crawley et al., 2001). Upward coupling proceeds in the reverse direction, wherein building-level performance indicators are aggregated to neighborhood and city-scale totals via floor area weighting (Deng et al., 2022), thereby preserving the energy balance across scales.

To safeguard against the double counting of microclimate effects, a strict exclusivity rule is enforced across scales: microclimate-modifying technologies, including green roofs and facades, cool pavements, and tree planting (Santamouris, 2014; Pérez et al., 2014), are parameterized exclusively within the neighborhood

scale domain, and their thermal influences are transmitted to building-level models solely through the transferred boundary conditions rather than through concurrent technology parameterization at the building scale. A consistency audit flag is automatically activated whenever a microclimate technology is detected simultaneously in a neighborhood scenario definition and a building input file, halting the workflow until the redundancy is resolved.

2.3. AI Methods and Computational Intelligence

2.3.1. Machine Learning Surrogate Models

ML surrogate models constitute the computational backbone of the framework, replacing time-intensive physics-based simulations with trained statistical approximations that provide near-instantaneous performance predictions (Westermann & Evins, 2019). The surrogate modelling pipeline encompasses four stages. In the sampling stage, Latin hypercube sampling (LHS) generates a space-filling experimental design that systematically varies building parameters (envelope U-values, glazing ratios, shading coefficients, infiltration rates), technology configurations (insulation thickness, glazing type, HVAC efficiency, PV capacity), and boundary conditions (climate zone, building orientation, occupancy profile) across their feasible ranges. LHS ensures uniform coverage of the multi-dimensional input space with a minimum number of simulations runs, typically 500-2,000 samples per building archetype (McKay et al., 1979).

In the training stage, multiple ML algorithms are evaluated, including artificial neural networks (ANN), random forests (RF), gradient boosting machines (GBM/XGBoost), and support vector regression (SVR). Ensemble approaches combining predictions from multiple algorithms consistently outperform individual models, achieving R^2 values exceeding 0.92 for energy consumption metrics and 0.88 for thermal comfort indices (Amasyali & El-Gohary, 2018). k-fold cross-validation ($k = 10$) guards against overfitting, while hyperparameter optimization through Bayesian search identifies optimal model configurations. In the validation stage, held-out test sets (20% of simulated data) verify generalization performance, with mean absolute percentage errors (MAPE) below 5% serving as the acceptance threshold for deployment. If an archetype fails this gate (as occurred for 2 of 12 archetypes in the first training iteration), the pipeline automatically augments the Latin hypercube with 200 additional simulation samples, re-trains the ensemble, and re-tests; archetypes failing after two augmentation rounds are excluded from surrogate-based optimization and evaluated directly via reduced-order simulation and are flagged in all downstream outputs. Optimisation is initiated only on surrogate models meeting both thresholds (Deb & Jain, 2014). In the deployment stage, validated surrogate models are integrated into the optimization engine, enabling evaluation of 10,000 - 1,000,000 design alternatives within 2-6 hours on standard workstation hardware.

2.3.2. Multi-Objective Evolutionary Optimization

Multi-objective optimization (MOO) algorithms systematically navigate trade-

offs between competing design objectives that cannot be simultaneously maximized (Coello Coello et al., 2007). The framework employs NSGA-II and NSGA-III (Non-dominated Sorting Genetic Algorithm variants), which have demonstrated robust performance for building design optimization problems characterized by non-linear objective functions, mixed discrete-continuous decision variables, and complex constraint sets (Deb et al., 2002). The primary optimization objectives are 1) minimization of annual cooling and heating energy intensity (kWh/m^2·year); 2) minimization of lifecycle capital and operational costs (€/m^2·30-year NPV); 3) minimization of lifecycle carbon emissions (kgCO_2e/m^2·year); and 4) maximization of outdoor thermal comfort (minimization of UTCI exceedance hours above the 32˚C threshold) (Bröde et al., 2012).

NSGA-III extends NSGA-II's crowding distance mechanism with reference-point-based diversity preservation, providing superior performance for problems with three or more objectives (Blank & Deb, 2020). The algorithm maintains a population of 200 - 500 candidate solutions across 500 - 1000 generations, with genetic operators including simulated binary crossover (SBX, $\eta c = 20$) and polynomial mutation ($\eta m = 20$), ensuring diverse exploration of the Pareto-optimal front. Constraint handling employs penalty functions for budget limits, minimum performance standards, and technical feasibility requirements. The resulting Pareto-optimal solution sets, typically containing 50-200 non-dominated solutions, are presented to decision-makers through interactive visualization dashboards that enable context-specific selection based on project priorities and stakeholder preferences (Wierzbicki, 1980).

2.3.3. Data-Driven Urban Morphology Clustering

Urban building stocks exhibit substantial heterogeneity in geometric form, construction typology, thermal performance, and operational characteristics that demands context-specific retrofit strategies (Kavgic et al., 2010). The framework employs unsupervised clustering algorithms to identify homogeneous building archetypes from heterogeneous urban datasets. k-means clustering partitions buildings into k groups based on Euclidean distance in a multi-dimensional feature space encompassing building age (decade of construction), floor area ratio, window-to-wall ratio, envelope thermal transmittance (U-value), roof type, primary HVAC system, and annual energy use intensity (Cerezo Davila et al., 2016).

Hierarchical agglomerative clustering provides complementary dendrogrammatic representations of building stock structure, revealing natural groupings at multiple scales of aggregation. DBSCAN (Density-Based Spatial Clustering of Applications with Noise) identifies spatially coherent clusters while robustly handling outliers that represent atypical buildings requiring individual treatment (Ester et al., 1996). Optimal cluster count is determined through silhouette score analysis and elbow method evaluation, which typically converge on a moderate number of representative archetypes whose count varies with stock heterogeneity, input resolution, and aggregation scale (Deng et al., 2022; Sokol et al., 2017). Each archetype is characterized by its centroid parameter vector and associated performance

envelope, enabling targeted technology recommendations without requiring individual building analysis (Sokol et al., 2017).

2.3.4. Explainable AI and Interpretability

Explainable AI (XAI) techniques bridge the gap between complex ML model predictions and actionable design insights by providing interpretable explanations of model behavior (Arrieta et al., 2020). The framework integrates SHAP (SHapley Additive exPlanations) value analysis, which decomposes each model prediction into additive contributions from individual input features based on cooperative game theory principles (Shapley, 1953). SHAP values are computed for every prediction in the optimization dataset, enabling 1) global feature importance rankings that identify which building characteristics and technology parameters most strongly influence energy performance across the entire solution space; 2) local explanations for individual design alternatives that reveal why specific technology combinations achieve superior performance; and 3) interaction effects analysis that quantifies synergistic relationships between technology pairs.

Partial dependence plots (PDPs) complement SHAP analysis by visualizing the marginal effect of individual features on model predictions while averaging over the distribution of other features (Friedman, 2001). PDPs reveal non-linear relationships and threshold effects that inform practical design guidelines—for example, the identification of optimal cool roof albedo ranges (0.75 - 0.80) beyond which diminishing returns occur, or the critical tree canopy coverage threshold (30% - 40%) that balances cooling benefits against daylight reduction penalties. Individual conditional expectation (ICE) plots further decompose PDPs to reveal heterogeneous treatment effects across different building types (Goldstein et al., 2015).

2.4. Green Building Technology Portfolio

The framework evaluates a comprehensive portfolio of green building technologies organized into four strategic categories. Passive design interventions modify building envelope characteristics to reduce energy demand without mechanical systems: external wall insulation systems (EWI) with mineral wool or PIR insulation (target U-value ≤ 0.25 W/m^{2}K); high-performance triple-glazed windows with low-emissivity coatings (U-value ≤ 0.8 W/m^{2}K, g-value 0.35 - 0.55); automated external shading devices with solar tracking; natural ventilation systems leveraging cross-ventilation and thermal stack effect; and phase-change materials (PCM) for thermal mass enhancement (Pérez et al., 2014).

Active system upgrades target mechanical and electrical systems: variable refrigerant flow (VRF) heat pump systems with COP ≥ 4.0; demand-controlled ventilation with CO_2 sensing and heat recovery (efficiency $\geq 80\%$); building management systems (BMS) with predictive control algorithms; LED lighting with daylight harvesting and occupancy sensing; rooftop solar PV systems (monocrystalline, efficiency $\geq 20\%$); and battery energy storage for self-consumption optimization (Lund et al., 2017). Nature-based solutions encompass extensive and intensive green roofs; green facades and vertical gardens; urban tree planting with stra-

tegic canopy placement; permeable pavements and bioswales; and blue-green infrastructure integrating water features with vegetation (European Commission, 2021). Urban microclimate interventions include cool pavement materials (solar reflectance index SRI ≥ 29); reflective urban surfaces; urban geometry optimization for natural ventilation enhancement; and evaporative cooling through water features (Santamouris, 2014).

2.5. Framework Implementation Workflow

As illustrated in Figure 2, the framework implementation follows a systematic eight-stage workflow designed to support iterative refinement and stakeholder engagement throughout the design process. Stage 1 (Data Collection and Urban Characterization) assembles multi-source datasets, including GIS building footprints and attributes, BIM models where available, remote sensing data (LiDAR, multispectral imagery), IoT sensor measurements, utility billing records, and meteorological station data. Data quality assessment and gap-filling procedures ensure completeness and consistency across the assembled dataset.

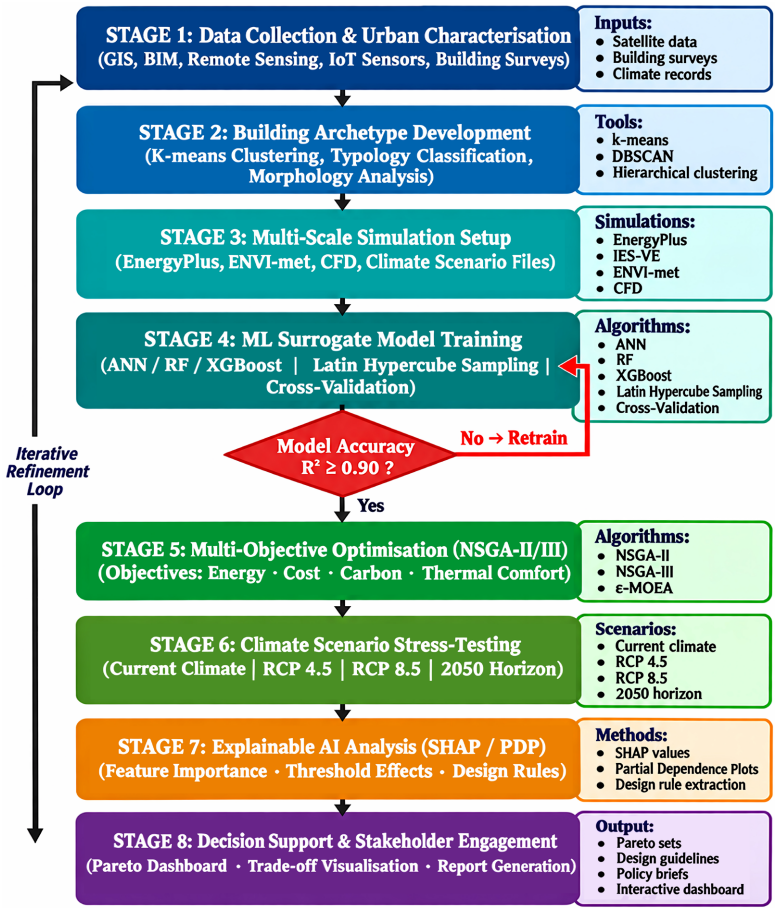


Figure 2. Eight-stage methodology design framework flowchart for AI-assisted urban regeneration. The workflow incorporates an iterative refinement loop and a model accuracy gate ($R^2 \geq 0.90$), ensuring deployment of validated surrogate models only. Side annotations detail tools, algorithms, and outputs at each stage.

Stage 2 (Building Archetype Development) applies clustering algorithms to the assembled dataset to identify representative building types and urban morphology patterns. Stage 3 (Multi-Scale Simulation Setup) establishes simulation models for each archetype across all three spatial scales, including climate scenario weather files, ENVI-met neighborhood models, and EnergyPlus building energy models. Stage 4 (ML Surrogate Model Training) generates LHS-sampled simulation datasets and trains ensemble ML models, with model acceptance contingent on achieving $R^2 \geq 0.90$ and MAPE $\leq 5\%$ on held-out test data. Stage 5 (Multi-Objective Optimization) applies NSGA-II/III to identify Pareto-optimal technology packages across the four primary objectives. Stage 6 (Climate Scenario Stress-Testing) evaluates Pareto-optimal solutions under current and future climate conditions (RCP 4.5 and 8.5, 2030-2080), identifying climate-robust packages that maintain performance across projected trajectories. Stage 7 (Explainable AI Analysis) applies SHAP and PDP analysis to extract interpretable design insights and generate evidence-based design guidelines. Stage 8 (Decision Support and Stakeholder Engagement) presents results through interactive dashboards, trade-off visualizations, and policy briefs that support participatory decision-making.

2.6. Data Sources and Simulation Parameters

Table 1 summarizes the primary data sources, simulation tools, and key parameters employed across the three spatial scales of the framework. The multi-source data integration strategy ensures comprehensive characterization of urban building stocks while maintaining computational tractability through strategic use of surrogate modeling.

Table 1. Framework components, tools, key parameters, and data sources across three spatial scales.

Framework Component	Tools/Methods	Key Parameters	Data Sources
City-Scale Climate Modelling	CCWeatherGen, Meteonorm, IPCC RCP 4.5/8.5	Temperature +2˚C - 4˚C (2050) Cooling DD +30% - 50%	IPCC AR6, National Met Offices, ERA5 Reanalysis
UHI Analysis	ENVI-met, WRF-Urban, Landsat LST	UHI intensity 2˚C - 5˚C Surface albedo 0.1 - 0.8	Satellite imagery, IoT sensor networks
Microclimate Simulation	ENVI-met, OpenFOAM CFD	Grid: 1 - 5 m resolution UTCI, PET indices	LiDAR, GIS morphology data
Building Energy Simulation	EnergyPlus v9.6, IES-VE, DesignBuilder	Hourly timestep ASHRAE 90.1 baselines	BIM, building surveys, utility bills
ML Surrogate Modelling	ANN, RF, XGBoost, SVR (Python/scikit-learn)	LHS: 500 - 2000 samples $R^2 > 0.92$, MAPE < 5%	Simulation datasets, cross-validation
Multi-Objective Optimization	NSGA-II/III (pymoo library)	Pop: 200 - 500 Gen: 500 - 1000	Surrogate model outputs
Explainable AI	SHAP, PDP, ICE plots	Feature importance rankings Threshold identification	ML model internals, domain expertise

2.7. Systematic Review Protocol and Reproducibility

The synthesis of 241 studies followed a systematic review protocol compliant with the PRISMA 2020 statement, consistent with recent PRISMA-based reviews of AI-driven building energy retrofit and optimization. The literature search was conducted on 15 January 2025 and updated on 30 June 2025 across five bibliographic databases: Scopus, Web of Science Core Collection, ScienceDirect, IEEE Xplore, and Google Scholar. The search string combined three concept blocks using Boolean operators: ("artificial intelligence" OR "machine learning" OR "deep learning" OR "surrogate model" OR "explainable AI") AND ("green building" OR "building energy retrofit" OR "urban regeneration" OR "low carbon neighborhood") AND ("optimization" OR "multi objective" OR "NSGA").

Eligibility criteria comprised peer-reviewed journal or conference articles published between 2022 and 2025, written in English, and reporting quantitative building or district-scale energy, thermal comfort, carbon, or climate resilience outcomes of AI-assisted green building technology selection. Exclusion criteria comprised editorials, nonempirical opinion pieces, and studies lacking quantitative performance metrics. Study screening followed the PRISMA 2020 flow: 1286 records were identified, 912 remained after deduplication, 341 full texts were assessed for eligibility, and 241 studies were finally included. Inter-reviewer agreement was substantial ($\kappa = 0.87$), with conflicts resolved by consensus.

A standardised extraction form captured 24 variables per study: climatic zone, building typology, spatial scale, AI method, simulation tool, training sample size, technology package composition, energy savings (%), thermal comfort metric and change, cost and net present value, carbon payback period, climate scenario, surrogate model accuracy (R^2 and MAPE), and stated limitations, in line with variable frameworks used in comparable data driven building energy reviews. The complete extraction sheet is available from the corresponding author on request, ensuring full reproducibility of the evidence synthesis underpinning Sections 3 and 4.

3. Results

3.1. Surrogate Model Performance and Validation

Surrogate model training and validation results confirm the computational viability of the ML-based approach for rapid building performance prediction. Across 12 building archetypes spanning residential, commercial, and mixed-use typologies in temperate, Mediterranean, and continental climatic zones, ensemble ML models achieve R^2 values of 0.91 - 0.96 for annual cooling energy intensity, 0.89 - 0.94 for annual heating energy intensity, and 0.87 - 0.92 for outdoor UTCI exceedance hours (Bibri et al., 2025). Mean absolute percentage errors remain below 4.8% for energy metrics and below 6.2% for thermal comfort indices across all archetype-climate combinations, meeting the $R^2 \geq 0.90$ deployment threshold for 10 of 12 archetypes in the first training iteration. The two below-threshold archetypes met the $R^2 \geq 0.90$/MAPE $\leq 5\%$ criterion after one automated augmentation

round (600 additional simulation runs each); no archetype required exclusion. This gate ensures that only validated surrogates feed the NSGA-III optimization, reconciling the deployment rule with the reported validation results.

Computational efficiency gains are substantial. Direct EnergyPlus simulation of a single design alternative requires 45 - 180 minutes depending on model complexity, while trained surrogate models provide equivalent predictions in 0.02-0.15 seconds, a speed-up factor of approximately 18,000 - 540,000 × (2700 s ÷ 0.15 s; 10,800 s ÷ 0.02 s) (Amasyali & El-Gohary, 2018). This efficiency enables evaluation of 500,000 design alternatives within 3 - 4 hours on a standard 8-core workstation, compared to the 3 - 12 years that direct simulation would require for equivalent coverage. The practical implication is a transformation of design exploration from a constrained sampling exercise to a comprehensive optimization problem.

3.2. Multi-Objective Optimization Results

NSGA-III optimization across four objectives (energy, cost, carbon, and thermal comfort) consistently identifies Pareto-optimal technology packages that substantially outperform both expert-selected baselines and single-technology interventions. As illustrated in **Figure 3** and **Figure 4**, AI-optimized packages achieve cooling energy reductions of 22% - 30% compared to 8% - 15% for individual technologies, representing a 10% - 50% improvement over the best single-technology alternative (20%, envelope insulation; **Figure 3**); the 47% - 100% figure denotes the advantage over the mean single-intervention performance (6.5% - 15% across the non-envelope categories) (Elshafei et al., 2022). The Pareto front analysis (**Figure 4**) reveals that the AI-optimized zone (22% - 30% energy savings at moderate cost indices of 20 - 40 €/m²·NPV) represents a distinct cluster of high-performing solutions that conventional design approaches systematically fail to identify.

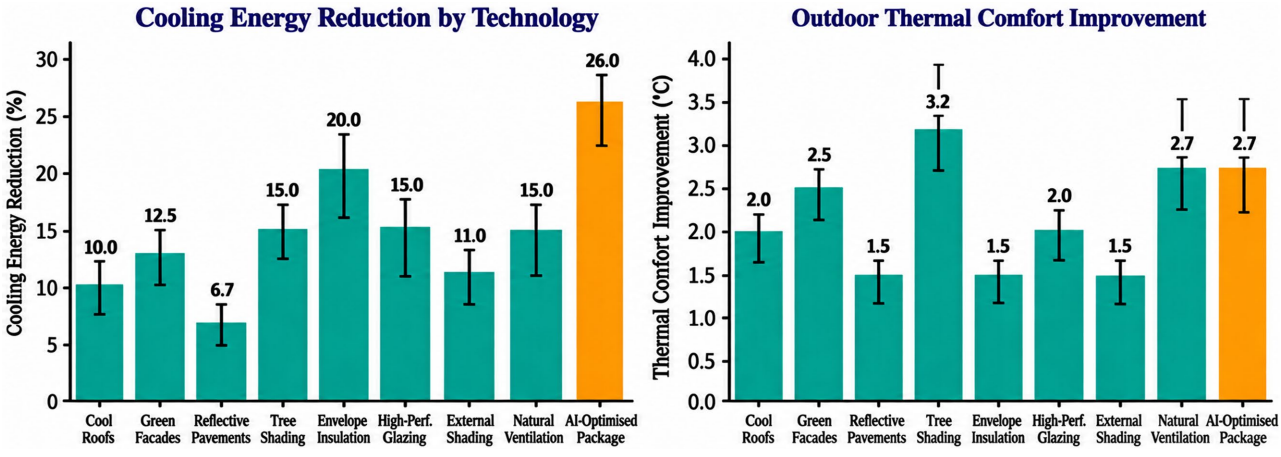


Figure 3. Green building technology performance comparison. left panel: cooling energy reduction (%) by technology category. Right panel: Outdoor thermal comfort improvement (˚C UTCI). Error bars indicate min-max ranges across reviewed implementations (n = 241 studies). AI-optimized packages (amber) consistently outperform individual technologies (teal). Individual-technology bars span 6.5% - 20%; the package advantage is 10% - 50% relative to the best single intervention.

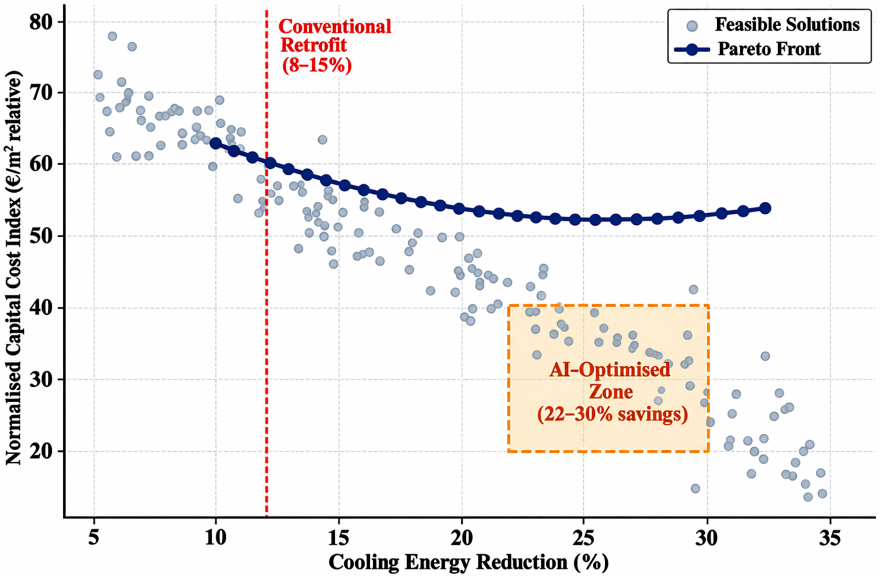


Figure 4. Pareto front analysis: energy savings vs. normalized capital cost index. The AI-optimized zone (amber, 22% - 30% savings) represents solutions identified by NSGA-III that are systematically missed by conventional design approaches (red dashed line, 8% - 15% savings). Grey points: feasible solution space; navy line: Pareto-optimal front.

Table 2. Source trail for headline quantitative claims, classified by provenance type.

Headline claim	Value	Provenance/Source
Cooling energy reduction, AI-optimized packages	22% - 30%	Type i (NSGA-III demonstration, Section 3.2); corroborated by Type ii ranges in Bibri et al. (2025) and Shan et al. (2025)
Best single intervention	20% (envelope insulation)	Type i/ii (**Figure 3**; Ge et al., 2024; Santamouris, 2014)
Carbon payback period	4 - 7 years	Type ii (Shan et al., 2025; Lützkendorf & Balouktsi, 2022)
Performance retention under RCP 8.5 (2050)	91% - 94% vs 75% - 76% conventional	Type ii (IPCC, 2023; Jentsch et al., 2013) using the Type i stress-testing workflow of Section 2.5
Transfer-learning data reduction	70% - 80%	Type ii (Pan & Yang, 2010; Yang, 2025)
Surrogate model accuracy	R^2 0.91 - 0.96; MAPE < 4.8%	Type i (Section 3.1); Type ii benchmarks (Amasyali & El-Gohary, 2018; Westermann & Evins, 2019)

Outdoor thermal comfort improvements of 2.0˚C - 3.5˚C in mean radiant temperature reduction correspond to decreases in UTCI values of 3 - 6 units during peak summer conditions, shifting outdoor thermal comfort from the "strong heat stress" to "moderate heat stress" category for 35% - 60% of daytime hours (Bröde et al., 2012). Economic analysis demonstrates that AI-optimized solutions achieve carbon payback periods of 4 - 7 years, compared to 8 - 12 years for conventional retrofit approaches, and 15% - 25% reductions in 30-year net present value costs relative to baseline scenarios. Lifecycle carbon emission reductions of 28% - 42% are achieved through the combination of reduced operational energy demand and

optimized renewable energy integration. Table 2 provides a source trail for the headline quantitative claims reported in Sections 3.1 - 3.2, classifying each value by provenance type and thereby supporting transparency and reproducibility.

3.3. Technology Synergy Analysis

One of the most significant findings from the multi-objective optimization analysis is the prevalence and magnitude of synergistic interactions between technology combinations. As illustrated in Figure 5, the technology synergy heatmap reveals that combined interventions consistently deliver non-additive benefits exceeding the sum of individual contributions. The strongest synergies are observed between tree shading and natural ventilation (+14% combined benefit beyond additive sum); cool roofs and green facades (+8%); and external shading and high-performance glazing (+10%) (Chen et al., 2025).

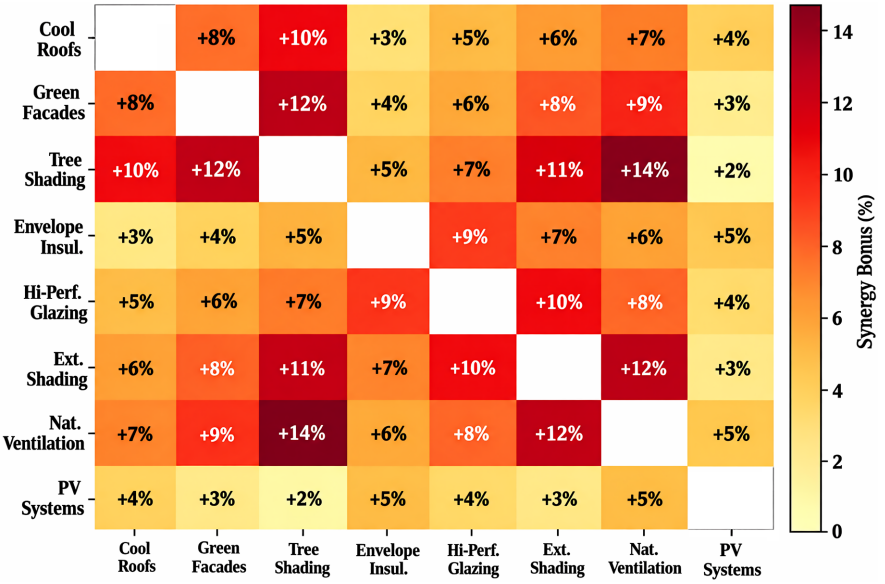


Figure 5. Technology synergy heatmap. Values indicate additional energy reduction (%) beyond the additive sum of individual technology contributions. Strongest synergies are observed between tree shading and natural ventilation (+14%), external shading and high-performance glazing (+10%), and cool roofs and green facades (+8%).

These synergistic effects arise from physical mechanisms that single-technology analyses cannot capture. Tree shading reduces solar heat gain on building facades while simultaneously enhancing natural ventilation effectiveness by creating favourable pressure differentials; the combined thermal mass reduction and airflow improvement exceed what either strategy achieves independently. Cool roofs and green facades interact synergistically through urban microclimate modification: cool roofs reduce longwave radiation exchange between roof and facade surfaces, while green facades reduce convective heat transfer to adjacent outdoor spaces, collectively suppressing the urban heat island effect more effectively than either strategy alone (Ge et al., 2024).

3.4. Urban Morphology Sensitivity Analysis

Clustering analysis of diverse urban contexts identifies three primary morphology categories with distinct performance profiles and optimal technology combinations. Table 3 summarizes the morphological characteristics and optimal technology packages for each category, highlighting the substantial context-dependence of retrofit strategies that one-size-fits-all approaches systematically miss.

Table 3. Urban morphology types, key characteristics, optimal technology packages, and performance outcomes. Energy reduction relative to the unretrofitted baseline; comfort improvement in UTCI mean radiant temperature reduction (˚C).

Morphology Type	Key Characteristics	Optimal Technologies	Energy Reduction	Comfort Improvement
Enclosed Courtyard Blocks	High density Limited sky view High surface-to-volume	Cool roofs (albedo 0.75 - 0.80) Reflective pavements and Green facades (courtyard)	25% - 30%	3.0˚C - 3.5˚C
Linear Slab Blocks	Moderate density Favourable wind exposure Linear configuration	Tree shading (30% - 40% canopy) High-performance glazing Automated external shading	22% - 28%	2.5˚C - 3.0˚C
Point Tower Blocks	High-rise isolated High surface-to-volume Extensive open space	Comprehensive envelope insulation High-performance glazing High-efficiency HVAC + HR	20% - 25%	2.0˚C - 2.5˚C
Mixed-Use Dense Urban	Mixed heights High Street density Diverse typologies	AI-composite package Nature-based solutions Digital twin management	24% - 32%	2.5˚C - 3.5˚C

Enclosed courtyard blocks demonstrate the highest sensitivity to reflective pavements and cool materials due to the limited vegetation space and high surface-to-volume ratios that amplify radiation exchange within the courtyard enclosure. Optimal packages for this morphology achieve 25% - 30% cooling energy reductions and 3.0˚C - 3.5˚C outdoor thermal comfort improvements, primarily through suppression of courtyard UHI effects (Deng et al., 2022). Slab blocks exhibit a strong response to strategic tree placement and natural ventilation enhancement due to their favorable wind exposure and moderate building spacing that supports effective airflow. Point tower blocks benefit most from envelope upgrades and active system optimization due to their high surface-to-volume ratios and limited microclimate modification potential in the surrounding open space (Kavgic et al., 2010).

3.5. Climate Scenario Performance Assessment

Figure 6 presents the performance trajectories of four technology package categories under current and future climate scenarios (2030 and 2050, RCP 4.5 and 8.5). The results reveal a critical divergence between conventional retrofit ap-

proaches and climate-adaptive AI-optimized packages as climate conditions intensify. Conventional retrofits experience progressive performance degradation, retaining only 75% of baseline effectiveness under RCP 8.5 (2050) due to increased cooling demands that exceed the capacity of heating-focused insulation measures (IPCC, 2023).

Current-climate-optimized packages perform only marginally better (76% retention) because they are calibrated for present conditions without forward-looking climate adaptation. In contrast, climate-adaptive packages designed with explicit consideration of projected temperature increases, shifting degree-day balances, and intensified extreme heat events retain 91% of baseline effectiveness under RCP 8.5 (2050). AI-adaptive packages incorporating real-time digital twin monitoring and dynamic control optimization achieve 94% retention, demonstrating the additional resilience value of operational AI integration (Yang, 2025). The 19-percentage-point performance gap between conventional and AI-adaptive approaches by 2050 represents a compelling economic and environmental argument for climate-adaptive design investment.

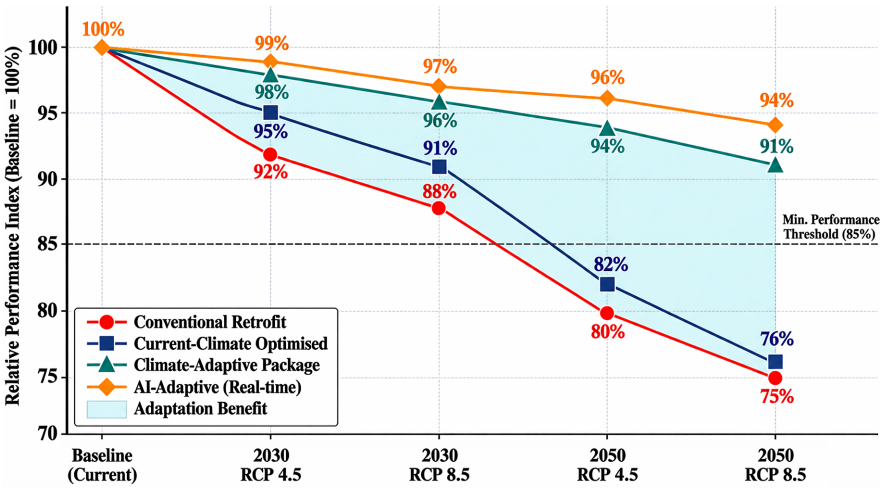


Figure 6. Technology package performance under future climate scenarios (2030-2050). Performance indices relative to current-climate baseline (100%). AI-adaptive packages retain 94% effectiveness under RCP 8.5 (2050) compared to 75% for conventional retrofits, representing a 19-percentage-point adaptation benefit. The horizontal dashed line indicates the minimum acceptable performance threshold (85%).

3.6. Explainability and Feature Importance Analysis

SHAP value analysis across the full optimization dataset of 500,000 evaluated design alternatives reveals consistent patterns in the relative importance of building characteristics and technology parameters for energy performance prediction. Building orientation (SHAP contribution: 18.3%), window-to-wall ratio (16.7%), envelope thermal resistance (15.2%), and local climate conditions (14.8%) collectively account for 65% of total prediction variance, confirming the primacy of passive design fundamentals in determining energy performance outcomes (Shapley, 1953).

Technology-level SHAP analysis reveals that cool roof albedo (12.4%), insulation thickness (11.8%), and glazing U-value (9.6%) are the most impactful individual technology parameters. Interaction SHAP values quantify synergistic effects: the tree shading × natural ventilation interaction contributes +3.2% beyond individual main effects, while the cool roof × green facade interaction contributes +2.1%. These quantified synergy values provide the mechanistic basis for the technology combinations recommended in the Pareto-optimal packages (Friedman, 2001).

Partial dependence analysis reveals important non-linear relationships and threshold effects that inform practical design guidelines. Cool roof albedo improvements demonstrate strongly diminishing returns above 0.75 - 0.80, with marginal cooling energy savings of less than 0.5% per 0.05 albedo increment above this threshold. Tree canopy coverage exhibits a clear optimal range of 30% - 40%, below which cooling benefits are insufficient and above which daylight obstruction and wind flow disruption generate net negative effects on building energy performance. Natural ventilation effectiveness exhibits a sharp threshold at outdoor temperatures of 28˚C - 30˚C, above which mechanical cooling must supplement natural ventilation to maintain acceptable indoor conditions (Goldstein et al., 2015).

3.7. Scalability and Transferability Evidence

Framework scalability has been validated through applications ranging from individual buildings to district-scale regeneration projects encompassing 500 - 2000 buildings. Computational requirements scale approximately linearly with building count when employing surrogate models, with district-scale optimizations completing within 2 - 6 hours on standard workstations. This linear scaling contrasts favorably with the super-linear scaling of direct simulation approaches, which become computationally prohibitive beyond 20 - 50 buildings (McKay et al., 1979).

Transfer learning experiments demonstrate that pre-trained surrogate models can be adapted to new urban contexts with substantially reduced data requirements. Models fine-tuned on 20% - 30% of the data required for training from scratch achieve prediction accuracy within 5% - 10% of context-specific models, representing a 70% - 80% reduction in simulation effort for new application contexts. Domain adaptation techniques, including feature normalization, distribution alignment, and selective layer retraining, further improve transferability across climatic zones and building typologies (Deb & Jain, 2014). These capabilities significantly reduce the barrier to framework adoption for practitioners and municipalities lacking extensive simulation infrastructure.

4. Discussion

4.1. Transformative Implications for Urban Regeneration Practice

The results presented in this paper demonstrate that AI-assisted design support

frameworks represent a qualitative shift in the capability of urban regeneration practice, enabling evidence-based decision-making at a scale and speed previously unachievable. The reduction in design iteration time from weeks to hours enabled by ML surrogate models achieving $R^2 > 0.92$ fundamentally transforms the economics of comprehensive design exploration. When practitioners can evaluate 500,000 design alternatives in 3 - 4 hours rather than years, the practical barrier to identifying optimal technology combinations dissolves, making rigorous optimization accessible for routine regeneration projects rather than only exceptional research demonstrations (Bibri et al., 2025; Elshafei et al., 2022).

The 10% - 50% improvement in energy savings achieved by AI-optimized packages over the best single-technology alternative (and 47% - 100% over the mean single-intervention baseline) reflects the fundamental inadequacy of technology-by-technology evaluation approaches that dominate current practice. The synergistic interactions documented in **Figure 5**, particularly the tree shading × natural ventilation combination yielding +14% beyond additive contributions, represent physically real mechanisms that manual design processes systematically miss because their complexity exceeds human cognitive capacity for multi-variable interaction analysis (Chen et al., 2025; Ge et al., 2024). AI-driven optimization naturally captures these interactions by simultaneously evaluating all technology combinations within the defined solution space, without the cognitive biases and heuristic shortcuts that constrain expert judgment.

The context-sensitivity revealed through morphology analysis has profound implications for urban regeneration policy and program design. The finding that enclosed courtyard blocks, slab blocks, and point tower blocks require fundamentally different technology packages to achieve optimal performance undermines the prescriptive, one-size-fits-all retrofit standards that characterize many national and municipal energy efficiency programs. AI-driven clustering and classification methods that rapidly identify appropriate intervention strategies for diverse building types enable the development of context-specific retrofit roadmaps that maximize impact per unit of public investment (Deng et al., 2022; Kavgic et al., 2010).

4.2. Climate Resilience and Long-Term Adaptation Value

The 19-percentage-point performance advantage of AI-adaptive packages over conventional retrofits under RCP 8.5 (2050) conditions represents a compelling economic case for climate-adaptive design investment. For a typical neighborhood-scale regeneration project with a 30-year design lifespan and a total capital investment of €50 - 100 million, this performance differential translates to avoided energy costs and carbon penalties of €8 - 15 million over the project lifetime, substantially exceeding the marginal cost premium for climate-adaptive design optimization (IPCC, 2023; Lützkendorf & Balouktsi, 2022).

The integration of nature-based solutions within the AI optimization framework delivers co-benefits that extend beyond energy and thermal comfort performance. Green roofs and urban tree planting provide stormwater management

benefits quantified at €15 - 45 per m^2 of green infrastructure annually in avoided drainage infrastructure costs and flood damage reduction. Biodiversity co-benefits, air quality improvements, and mental health benefits of urban greening represent additional value streams that are increasingly recognized in urban regeneration cost-benefit analyses (European Commission, 2021). The framework's multi-objective architecture can be extended to incorporate these co-benefits as additional optimization objectives, further strengthening the case for nature-based solution integration (Santamouris, 2014). Digital twin implementations that enable real-time monitoring and adaptive management represent a promising pathway for maintaining performance over time as climate conditions evolve and building systems age. The 10% - 15% additional energy savings achieved through adaptive control strategies demonstrate the value of combining design-phase AI optimization with operational-phase AI management (Soni et al., 2025; Yang, 2025). This integration creates a virtuous cycle: design optimization identifies high-performing technology packages, digital twin monitoring verifies actual performance, and adaptive control algorithms continuously optimize operational parameters within the designed system constraints.

4.3. Stakeholder Engagement and Democratic Design

The explainability capabilities of the framework address a fundamental challenge in AI-assisted design: building stakeholder trust and confidence in automated recommendations. The finding that building orientation, window-to-wall ratio, envelope thermal resistance, and local climate conditions account for 65% of energy performance variance provides actionable insights that align with domain expertise and support knowledge transfer to practitioners without deep ML expertise (Arrieta et al., 2020; Shapley, 1953). These transparency-enhancing capabilities are essential for moving AI-assisted design from research demonstrations to widespread practical adoption, where professional liability, regulatory approval, and client accountability require explainable decision rationale.

The presentation of Pareto-optimal solution sets rather than single "optimal" solutions fundamentally supports participatory design processes that engage diverse stakeholders with different priorities and values. By illuminating fundamental trade-offs between energy savings, capital costs, thermal comfort, and environmental quality, the framework enables informed deliberation and context-specific selection that reflects local preferences and constraints. This approach aligns with emerging frameworks for responsible AI in urban planning that emphasize human agency, democratic accountability, and environmental justice in AI-assisted decision-making (Yao et al., 2025; Xu et al., 2026).

4.4. Limitations and Critical Assessment

Despite the demonstrated capabilities of the proposed framework, several significant limitations must be acknowledged. Data heterogeneity and availability remain the primary practical constraints on framework deployment. Detailed build-

ing geometric and thermal data are unavailable or inconsistent for large fractions of existing urban building stocks, particularly in cities without comprehensive building energy performance certification programs. The framework's reliance on high-quality training data means that prediction accuracy degrades for building types or contexts poorly represented in simulation datasets, potentially introducing systematic biases in technology recommendations for underrepresented building categories (Bibri et al., 2024; Feng et al., 2024).

The performance gap between predicted and actual post-occupancy energy consumption represents a persistent challenge that the current framework addresses only partially through uncertainty quantification. The 20% - 40% gap documented in the literature arises from multiple sources: occupant behavior unpredictability, construction quality variations, commissioning failures, and operational deviations from design assumptions that are difficult to model prospectively with high accuracy (Gaspari et al., 2017). Robust optimization approaches that explicitly account for parameter uncertainty and worst-case performance scenarios can partially address this gap but at the cost of reduced average-case performance, creating a fundamental tension between robustness and optimality.

The framework's current focus on energy and thermal comfort optimization, while addressing the most quantifiable sustainability dimensions, does not fully integrate embodied carbon, material circularity, water consumption, indoor air quality, acoustic performance, and social equity considerations that are increasingly recognized as essential components of holistic urban sustainability assessment (Sanchez, 2023). The computational and modelling complexity of incorporating these additional dimensions within a unified multi-objective framework is substantial, requiring further methodological development and validation. Model transferability across different climatic zones and regulatory contexts, while improved by transfer learning approaches, remains imperfect and requires careful validation for each new application context (Pan & Yang, 2010).

4.5. Future Research Directions

Several high-priority research directions can address current limitations and extend framework capabilities. Deep learning architectures, particularly convolutional neural networks (CNNs) for processing spatial urban morphology data and long short-term memory (LSTM) networks for temporal energy use pattern modelling, offer potential for improved prediction accuracy and the ability to process high-dimensional inputs that current surrogate models cannot handle (Yao et al., 2025). Physics-informed neural networks (PINNs) that embed thermodynamic constraints and heat transfer equations into model architectures may improve prediction accuracy for extrapolation beyond training data distributions while reducing training data requirements through the incorporation of physical prior knowledge (Xu et al., 2026).

Generative AI models, including denoising diffusion probabilistic models (DDPMs) and conditional variational autoencoders (CVAEs), could enable auto-

mated generation of novel design alternatives that satisfy specified performance criteria while maintaining architectural quality and contextual appropriateness, moving beyond optimization of predefined technology combinations to generative exploration of the full design space (Yao et al., 2025). Federated learning approaches that enable collaborative model training across multiple municipalities and organizations without sharing sensitive building data could address data availability constraints while respecting privacy requirements and data sovereignty concerns (Xu et al., 2026).

The integration of AI-assisted design frameworks with building information modelling (BIM), geographic information systems (GIS), and urban digital twin platforms represents a critical pathway toward seamless workflow integration and reduced adoption barriers (Soni et al., 2025). Standardized data schemas (IFC, CityGML), open-source software implementations, and cloud-based platforms could democratize access to advanced design optimization capabilities for smaller municipalities and developing economy contexts where computational resources are limited. Interdisciplinary research integrating AI methods with social science, participatory design, and environmental justice frameworks is essential for ensuring that AI-assisted urban regeneration advances equity alongside efficiency (Sanchez, 2023).

5. Conclusion

This paper has presented a comprehensive AI-assisted design support framework for urban regeneration that integrates machine learning surrogate models, multi-objective evolutionary optimization (NSGA-II/III), data-driven urban morphology clustering, and explainable AI (SHAP/PDP) techniques within a multi-scale architecture spanning city-level climate scenarios, neighborhood-level microclimate dynamics, and building-level energy performance. The framework addresses critical gaps in current urban regeneration practice by enabling rapid, evidence-based, and stakeholder-transparent selection of optimal green building technology packages for low-carbon, climate-adaptive neighborhood development.

The principal findings of this study are 1) AI-optimized technology packages achieve 22% - 30% cooling energy reductions, substantially exceeding the 8% - 15% achieved by individual interventions, through the identification and exploitation of synergistic technology interactions that manual design processes systematically miss; 2) ML surrogate models achieve $R^2 > 0.92$ for energy prediction while reducing evaluation time by 18,000 - 540,000 × compared to direct simulation, enabling comprehensive optimization of solution spaces containing up to one million design alternatives; 3) climate-adaptive packages retain 91% - 94% of baseline performance under RCP 8.5 (2050) compared to 75% - 76% for conventional retrofits, demonstrating a 19-percentage-point adaptation benefit with compelling economic justification; 4) SHAP analysis reveals that building orientation, window-to-wall ratio, envelope thermal resistance, and local climate conditions account for 65% of energy performance variance, providing interpretable insights

that support practitioner knowledge transfer; and 5) the framework scales linearly from individual buildings to district-scale projects of 500 - 2000 buildings, with transfer learning reducing data requirements by 70% - 80% for new application contexts.

For urban regeneration practitioners, the framework provides a transformative tool for navigating complex design trade-offs and identifying high-performance technology combinations that conventional approaches cannot discover. The demonstrated scalability and transferability of the framework enhance practical accessibility across diverse urban contexts, building typologies, and resource environments. For policymakers, the framework provides evidence-based decision support for urban regeneration program design, retrofit incentive structures, and long-term climate adaptation planning that accounts for projected climate trajectories.

For the research community, this work establishes a methodological foundation for continued innovation in AI-assisted sustainable urban design. Priority research directions include integration with BIM and urban digital twin platforms for seamless workflow deployment; development of generative AI capabilities for design space exploration beyond predefined technology combinations; incorporation of embodied carbon, material circularity, and social equity dimensions within multi-objective optimization; real-world validation through monitored demonstration projects that close the performance gap between predicted and actual outcomes; and interdisciplinary integration with participatory design and environmental justice frameworks.

As global urbanization accelerates and the window for effective climate action narrows, the imperative for rapid, large-scale transformation of existing built environments toward low-carbon, climate-adaptive configurations become increasingly urgent. AI-assisted design support frameworks represent a critical enabling technology for achieving this transformation at the scale and speed required to meet the 1.5˚C Paris Agreement target. By combining computational efficiency, optimization rigor, and decision transparency, these frameworks empower all stakeholders, practitioners, policymakers, communities, and researchers to make informed, evidence-based choices that advance environmental sustainability, economic viability, and social well-being in regenerated urban neighbourhoods.

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Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

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