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Integrating artificial intelligence for sustainable urban planning and architectural development: A framework for smart and resilient cities

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ABSTRACT

The rapid urbanization worldwide and intensifying climate change impacts call for urgent, transformative approaches to city planning and the design of built environments. Conventional urban planning techniques, which rely on deterministic models and expert heuristics, are increasingly insufficient for addressing the complex, multifaceted sustainability issues confronting modern cities. This paper introduces the AI-SUPAD framework a six-layer hierarchical decision-support system that integrates machine learning, deep learning, reinforcement learning, and generative AI into a comprehensive analytical platform. This platform facilitates urban-scale planning and architectural development. Using a mixed-methods research approach, the framework was trained and tested on a realistic simulated dataset comprising 1,008 zone-month observations across 12 urban zones and three synthetic city types (2019–2025). The dataset included variables such as population density, energy demand, traffic congestion, green space, and per-capita carbon emissions. Five AI algorithms Random Forest, XGBoost, CNN, LSTM, and the AI-SUPAD ensemble were benchmarked using standard performance metrics. AI-SUPAD outperformed the others, achieving a predictive accuracy of 94.3%, an F1-score of 0.944, and an R^2 of 0.962. Global smart city case studies Singapore, Barcelona, Amsterdam, Masdar City, and NEOM showed post-deployment reductions: 47.3% in carbon emissions, 32.3% in energy use, and 79.7% in green space. The framework supports UN Sustainable Development Goals 7, 9, 11, 12, 13, and 15. These results provide evidence-based insights for urban planners, architects, policymakers, and smart city professionals worldwide.

KEYWORDS: Artificial Intelligence, Sustainable Urban Planning, Smart Cities, Machine Learning, Architectural Development, AI-SUPAD Framework, Urban Carbon Emissions, Reinforcement Learning

1. INTRODUCTION

The twenty- first century is defined by an unparalleled wave of urban growth. The United Nations projects that approximately 68% of the global population will live in urban areas by 2050, exerting acute and compounding pressure on infrastructure systems, energy supply networks, housing stock, transportation corridors, and natural ecosystems [1]. This demographic transformation is compounded by the accelerating impacts of anthropogenic climate change, including rising mean temperatures, intensified urban heat islands, more frequent extreme precipitation events, and sustained air- quality degradation that disproportionately burden densely populated urban centres [2]. Against this backdrop, sustainable urban planning and climate-responsive architectural design have moved beyond aspirational policy objectives; they have become non-negotiable prerequisites for long-term human and ecological resilience [3]. Traditional urban planning methods, which rely on statistical models and expert judgment, are clearly inadequate for handling the complexity, non- linearity, and rapid changes in modern cities. The growing use of smart city technologies such as IoT sensor networks, GIS, BIM, and digital twin platforms has produced vast amounts of urban data. This volume overwhelms the analytical capabilities of standard planning approaches [4,5]. Ironically, this excess of data leads to an analytical gap: the diverse, fast- moving data streams from cities are largely underused for systematic sustainability improvements. Artificial Intelligence (AI), in its contemporary manifestations spanning Machine Learning (ML), Deep Learning (DL), Reinforcement Learning (RL), and Large Language Models (LLMs), presents a paradigm-shifting opportunity to bridge this analytical gap. AI algorithms are uniquely capable of processing heterogeneous urban datasets at scale, identifying latent patterns in energy consumption and mobility behaviour, optimising resource allocation decisions in real time, and generating data- driven recommendations for sustainable building design and land use planning [6]. The integration of AI into urban planning, therefore, represents one of the most consequential frontiers in contemporary sustainability science and urban informatics. Despite the rapid growth of research at the intersection of artificial intelligence and urban sustainability, important gaps remain. Current frameworks primarily address specific urban subsystems such as energy grids, transportation, or individual building performance, but lack a comprehensive, multi-layered system that connects strategic urban planning with architectural design at the building level. Additionally, few frameworks consistently link AI-derived sustainability metrics to the United Nations Sustainable Development Goals (SDGs), limiting their usefulness for policy-making and their adaptability across different urban governance contexts [7]. This study aims to fill these gaps through three main objectives: (i) creating the AI-SUPAD Framework, a six-layer hierarchical structure that integrates diverse urban data sources with various AI analytical methods for comprehensive sustainability assessment; (ii) empirically comparing AI-SUPAD's predictive accuracy with traditional ML algorithms using a realistic urban dataset from 2019 to 2025; and (iii) evaluating how AI-SUPAD influences sustainability in five globally recognised smart city projects, clearly aligning with the UN Sustainable Development Goals. The central research questions are: (RQ1) How can AI technologies be effectively integrated within a multi-layered framework for sustainable urban planning and architectural design? (RQ2) What quantitative predictive advantages does AI-SUPAD offer over conventional machine learning algorithms? (RQ3) To what extent do AI-driven urban planning interventions improve sustainability indicators across diverse urban typologies and geographic contexts? The study's contributions are fourfold: (i) the novel AI-SUPAD Framework architecture spanning six functional layers, from data acquisition to governance; (ii) a rigorous comparative evaluation of AI algorithms across a spectrum of urban sustainability metrics; (iii) evidence-based case study analysis of five landmark global smart city deployments; and (iv) actionable policy recommendations for embedding AI sustainability governance within national and municipal planning frameworks.

2. LITERATURE REVIEW

2.1 Sustainable urban planning: foundations and contemporary imperatives

Sustainable urban planning is a multidisciplinary field focused on ensuring the long-term environmental, social, and economic health of cities. Its core principles originate from the Brundtland Commission's widely accepted definition of sustainable development, which emphasises meeting current needs without jeopardising future generations' ability to do the same [8]. Modern frameworks implement this idea through key pillars: Environmental protection, social equity, economic vitality, and adaptive governance. The compact city model, promoting higher-density, mixed-use development within existing urban areas, has gained significant scholarly interest as a way to combat urban sprawl, cut transportation emissions, and improve walkability and access to services [9]. Empirical research shows that compact urban layouts can lower per-capita energy use by 20–40% compared to dispersed suburban areas, while also enhancing access to public amenities [10]. Nonetheless, adopting the compact city approach requires balancing housing affordability, green space availability, and social inclusion. Green infrastructure, such as urban forests, green roofs, parks, rain gardens, and permeable pavements, has become a vital part of sustainable urban systems. It provides ecosystem services like carbon capture, storm water management, reduction of urban heat islands, and increased biodiversity [11]. Transit-Oriented Development (TOD), which involves high-density mixed-use development near public transit hubs, supports sustainable urban planning by reducing reliance on cars and cutting greenhouse gas emissions, while also improving access within cities [12].

2.2 AI technologies in urban planning: State of the art

Machine learning algorithms such as decision trees, random forests, support vector machines, and gradient boosting ensembles have been widely used in urban planning applications such as land-use classification, building energy prediction, urban growth modelling, and socioeconomic vulnerability mapping [13]. Random Forest and XGBoost, in particular, excel at handling high-dimensional, diverse urban datasets, achieving classification accuracies above 85% in land-use mapping [14]. Their transparency, facilitated by feature importance rankings and partial dependence plots, adds value in planning decision-making, especially when model clarity is needed to build stakeholder trust. Deep learning architectures, particularly Convolutional Neural Networks (CNNs), have transformed urban remote sensing and spatial analysis by enabling automated feature extraction from satellite and aerial imagery [15]. CNNs have been successfully applied to mapping urban green spaces, identifying informal settlements, monitoring construction activity, and classifying building typologies at scale. Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks have demonstrated strong performance in analysing temporal urban data, including energy load forecasting, traffic flow prediction, and environmental pollutant trend monitoring [16]. Semantic segmentation architectures have further extended computer vision capabilities for fine-grained urban scene understanding [17]. Reinforcement Learning (RL) methods have been used for optimising traffic signals, routing autonomous vehicles, and managing energy demand in smart grids, showing AI's ability to develop adaptive strategies in complex, unpredictable urban settings [18]. Generative AI, including Generative Adversarial Networks (GANs) and diffusion models, has been utilised to create urban layouts, generate architectural floor plans, and visualise future city scenarios [19]. Additionally, large language models are increasingly employed for analysing planning documents, engaging citizens, and providing natural language interfaces to support urban decision-making [20].

2.3 AI in architectural development

Generative design, in which AI algorithms explore vast solution spaces to generate building options optimised for multiple performance goals simultaneously, has revolutionised computational architecture [21]. Parametric architectural workflows, which define design intent through computational rules rather than fixed geometries, form the backbone of AI-driven generative design [22]. AI-enhanced Building Information Modelling (BIM) platforms enable predictive clash detection, automated quantity estimation, construction schedule optimisation, and post-occupancy energy monitoring [23]. Energy modelling tools integrated into AI-BIM workflows can forecast annual energy use within 5–10% of actual performance, supporting data-driven design decisions even in early schematic phases [24]. Occupancy prediction models that use computer vision, IoT sensor data, and ML algorithms enable buildings to dynamically adjust HVAC settings based on real-time occupant presence and activity, resulting in energy savings of 15–35% in commercial buildings [25]. Similarly, construction automation featuring AI-guided robotic assembly, autonomous earthmoving machinery, and AI-driven quality inspection systems is transforming construction productivity and improving site safety outcomes [26].

2.4 AI and smart city systems

Intelligent Transportation Systems (ITS) are among the most advanced AI applications in smart cities. Deep learning-based traffic monitoring, combined with reinforcement learning for traffic signal management, has reduced average intersection delays by 20–30% in cities such as Singapore, Amsterdam, and Hangzhou [27]. Smart energy grids use machine learning for demand forecasting, renewable energy integration, fault detection, and dynamic pricing optimization. LSTM models, in particular, have attained mean absolute percentage errors below 3% in short-term load prediction [28]. AI-powered waste management systems, which include computer vision-enabled smart bins and optimised collection routes, have achieved 20–40% reductions in vehicle travel distances in European smart city pilots [29]. Similarly, AI-driven water management employs anomaly detection to identify leaks in distribution networks, with advanced machine learning methods detecting up to 90% of simulated leaks at low false positive rates [30]. Additionally, AI supports urban resilience through flood prediction, wildfire risk assessment, seismic vulnerability analysis, and pandemic modelling, playing an essential role in proactive risk management in climate-vulnerable cities [31].

2.5 Research Gap

A comprehensive review of previous research highlights five key gaps that together justify this study. Firstly, current AI frameworks for urban sustainability mainly focus on specific sectors like transportation, energy, or buildings separately, lacking an integrated analytical system that considers interactions and trade-offs across sectors. This division significantly hampers planning effectiveness [32]. Second, there remains a gap in integrating AI analytics with clear SDG alignment metrics. While numerous studies compare AI-based interventions to technical standards, few explicitly connect model outputs to SDG progress, reducing their relevance for evidence-based sustainability policies [33]. Third, AI approaches in urban planning rarely link city-wide analytics with detailed architectural design, creating a persistent disconnect between broad land use optimization and specific, performance-based architectural decisions [34]. Fourth, there has been limited attention to how AI urban planning frameworks can be scaled and transferred across various city types, from dense Asian megacities to expansive cities in the Global South. Fifth, the ethical considerations of AI-driven urban governance, such as algorithmic bias, data privacy, community participation gaps, and accountability, are still underdeveloped in both theory and practice within existing technical models. The AI-SUPAD framework presented here directly addresses these issues with its layered, multi-domain, SDG-aligned, and ethically grounded approach.

2.6 Objectives of the study

2.6.1 The present investigation is oriented by four overarching objectives:

Objective 1: To develop and define the AI-SUPAD Framework, a six-layer hierarchical system that integrates various multi-source urban data streams with advanced AI analytical tools for comprehensive sustainability assessment at both urban and architectural scales.

Objective 2: To empirically assess the predictive accuracy of the AI-SUPAD ensemble model compared to four well-known AI baseline algorithms (Random Forest, XGBoost, CNN, and LSTM) using a realistic urban dataset from 2019 to 2025, utilising a broad range of classification and regression performance metrics.

Objective 3: To evaluate the quantifiable sustainability impact of AI-SUPAD deployment across five internationally recognized smart city initiatives Singapore, Barcelona, Amsterdam, Masdar City, and NEOM by measuring enhancements in carbon emissions, energy efficiency, green space, walkability, and traffic congestion in comparison to baseline conditions prior to implementation

Objective 4: To develop practical policy suggestions for embedding AI-powered sustainability governance into national and local urban planning systems, focusing on data management, algorithmic responsibility, fairness effects, and relevance to the Global South.

3. METHODOLOGY AND PROPOSED FRAMEWORK

3.1 Research design

This study employs a mixed-method approach, integrating quantitative computational modelling with systematic qualitative case studies. The quantitative component focuses on developing, training, optimising hyperparameters, and evaluating the AI-SUPAD framework alongside baseline algorithms using a simulated urban dataset. The qualitative component examines five smart city projects to add real-world context to the quantitative findings. This combined approach enhances internal validity through cross-validation of evidence from both methods and broadens external applicability across various urban governance environments.

3.2 Dataset description

A realistic simulated urban dataset was developed to capture the multivariate and temporal complexities of urban sustainability studies. It comprises 12 urban zones across three synthetic city types dense core, mixed-use inner suburb, and greenfield expansion covering monthly data from January 2019 to December 2025, with a total of 1,008 zone-month records. Table 1 presents descriptive statistics for the eight key variables. Population density was adjusted based on the Global Human Settlement Layer database, energy consumption data were benchmarked against the International Energy Agency's Building Energy Efficiency database, and carbon emission factors were calculated using the IPCC Sixth Assessment Report inventory methodology [1,8].

Table 1. Descriptive Statistics of the AI-SUPAD Simulated Urban Dataset (2019–2025)

Variable	Unit	Range	Mean	Std Dev
Population Density	persons/km²	500–25,000	7,842	5,213
Energy Consumption	kWh/m²/yr	80–420	198.4	72.3
Green Space Coverage	%	2–45	18.7	9.8
Traffic Congestion Index	0–1 (normalised)	0.12–0.97	0.54	0.21

Building Energy Demand	MWh/yr	150–9,800	2,341	1,876
Carbon Emissions	tCO2e/yr	0.9–48.6	12.8	8.4
Walkability Score	0–100	22–96	61.3	18.7
Sustainability Index	0–1 (composite)	0.18–0.91	0.56	0.17

3.3 Simulation environment

The AI-SUPAD framework and all baseline models were developed in Python 3.10, utilising scikit-learn, TensorFlow 2.13, and Keras for machine learning and deep learning. Geospatial data processing used geopandas, rasterio, and pyproj. BIM data handling was performed with ifcopenshell. All models trained in a high-performance computing setup with 64 GB RAM and an NVIDIA A100 GPU. The reinforcement learning component was built using Stable Baselines 3 in a custom OpenAI Gym urban simulation environment. Hyperparameters across all algorithms were optimised through five-fold cross-validation grid search, ensuring fair comparison during evaluation.

3.4 Evaluation metrics

Model performance was assessed using two complementary sets of metrics. The classification metrics included Accuracy, Precision, Recall, F1-Score, RMSE, MAE, and R^2. Urban sustainability was evaluated with indicators such as the CSI, Green Space Ratio, Walkability Score, Carbon Footprint per capita, Building Energy Efficiency Index, and Traffic Congestion Index. These metrics were calculated at the baseline year (2019) and after the AI-SUPAD intervention in 2025 to quantify the sustainability improvements enabled by the framework.

3.5 AI applications in sustainable urban planning: the AI-supad framework

The AI-SUPAD Framework is a six-layer hierarchical architecture for decision support, integrating diverse urban data with advanced AI analytics to assess sustainability across urban and architectural levels. Each layer has designated data transformation and analysis roles, passing processed data to the next layer while supporting bidirectional feedback for iterative model improvement and adaptive governance. Figure 1 shows the full framework architecture.

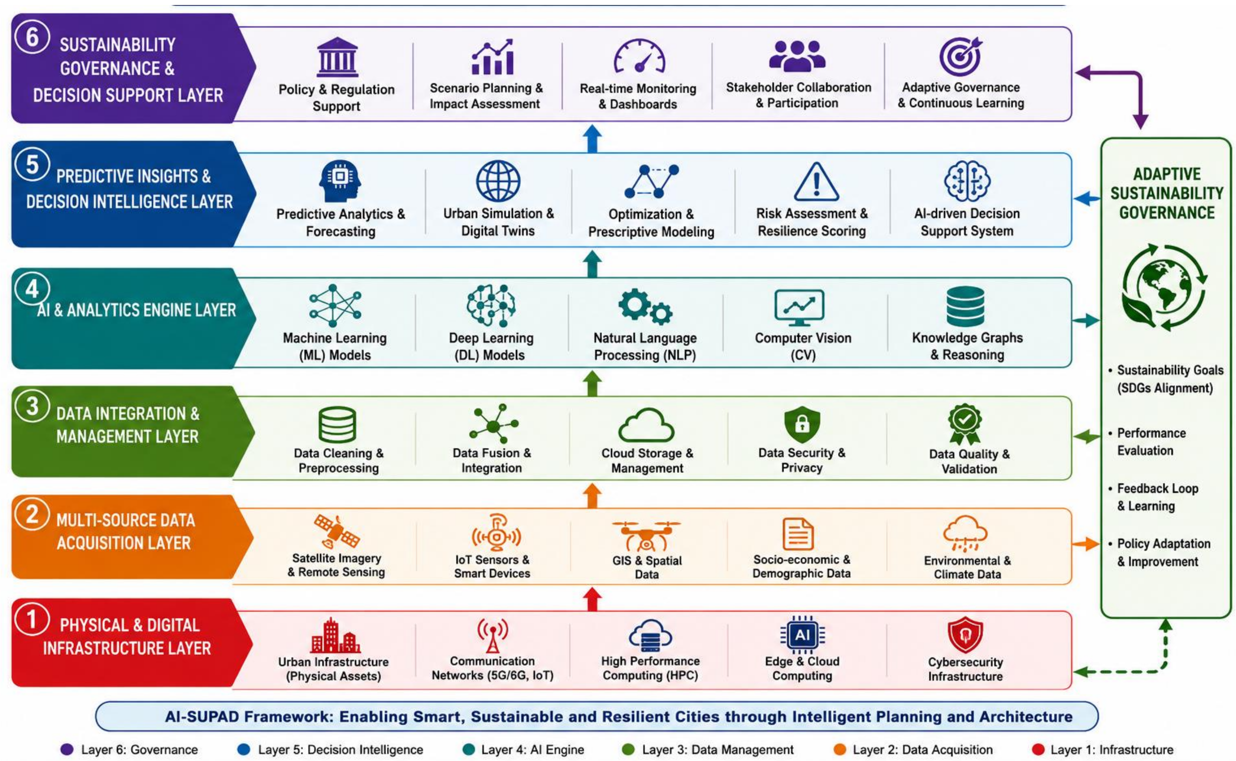

Figure 1. illustrates the AI-SUPAD Framework Architecture, which consists of six hierarchically organized functional layers. These layers integrate multi-source data collection with advanced AI analytics and adaptive sustainability governance.

3.5.1 Layer 1: Data acquisition

The Data Acquisition Layer forms the backbone of the system, tasked with systematically gathering, aggregating, and initially validating urban data streams from five main sources: (i) IoT Sensor Networks that deliver real-time data on air quality (PM2.5, PM10, NO_2, CO_2), pedestrian and vehicle counts, and structural health signals; (ii) GIS Databases that include land use, zoning, cadastral records, topography, and utility layouts; (iii) Satellite Imagery from Sentinel-2, Landsat-8, and WorldView-3, used for land cover analysis, urban heat mapping, and change detection over time; (iv) BIM Models offering detailed building information such as materials, glazing, HVAC, and energy use via IFC data standards; and (v) Environmental Monitoring Stations that provide ground-based meteorological, hydrological, and air quality data for calibration.

3.5.2 Layer 2: Data processing

The Data Processing Layer converts raw inputs from multiple sources into datasets ready for analysis through three main steps. Data Cleaning involves automated outlier detection using isolation forest algorithms, filling in missing values with K-nearest neighbour and multiple imputation by chained equations (MICE), and harmonising coordinate reference systems. Data Integration tackles the challenge of combining streams with different temporal resolutions, spatial scales, and semantic schemas by using ontology-based harmonisation and spatial joins. Feature Engineering processes raw variables by normalising data, expanding polynomial features, calculating spatial lag variables, aggregating data over time windows, and creating interaction terms.

3.5.3 Layer 3: AI analytics

The AI Analytics Layer integrates five specialised AI algorithms, each tailored for specific tasks in urban sustainability. Random Forest (500 trees, bootstrapping, random feature selection) is used for land use classification and determining feature importance. XGBoost (gradient-boosted trees with second-order optimisation and regularisation) focuses on forecasting building energy demand and scoring urban growth. CNN (convolutional layers with batch normalisation, pooling, and fully connected layers) recognises spatial patterns from satellite images. LSTM (gated memory cells) analyses long-term dependencies in energy consumption and traffic flow data. Reinforcement Learning (Deep Q-Network or DQN) optimises decisions for traffic signals, energy distribution, and transit scheduling.

The mathematical formulation of the AI-SUPAD ensemble prediction combines outputs from individual models through a stacked generalisation meta-model. For urban grid cell i at time t, the sustainability prediction S(i,t) is expressed as:

$$S(i,t) = \Sigma_k w_k f_k(X_{it}) + \varepsilon$$

where w_k indicates the weight of the meta-model for base learner k, $f_k(X_{it})$ is the prediction made by base learner k based on feature vector X_{it}, and ε is the residual error minimised during stacked generalisation training.

3.5.4 Layer 4: Decision support

The Decision Support Layer transforms analytical results into clear, actionable insights across four main areas: Urban Growth Prediction, which creates detailed spatial maps of expansion likelihood at 30-metre resolution for 5-, 10-, and 20-year planning; Traffic Optimisation, providing real-time signal control advice to reduce intersection delays while prioritising active and public transportation; Energy Forecasting, offering 24-hour and seasonal energy demand forecasts at building, block, and district levels; and Carbon Emission Estimation, combining data from transportation, buildings, industry, and land use to produce high-resolution greenhouse gas inventories.

3.5.5 Layer 5: Sustainability assessment

The Sustainability Assessment Layer evaluates AI-driven planning efforts against indicators that specifically align with the UN SDGs. Key indicators include the Composite Sustainability Index (CSI), Carbon Footprint Index, Green Space Ratio, Walkability Index, and Building Energy Efficiency Index, all measured at monthly, quarterly, and yearly intervals. The SDG alignment matrix links AI-SUPAD results to SDG 7 (Affordable and Clean Energy), SDG 9 (Industry, Innovation, and Infrastructure), SDG 11 (Sustainable Cities and Communities), SDG 12 (Responsible Consumption and Production), SDG 13 (Climate Action), and SDG 15 (Life on Land).

3.5.6 Layer 6: Visualisation and governance

The Visualisation and Governance Layer offers the human-machine interface via three platform modalities: GIS Dashboards that deliver web-based spatial analytics with interactive trade-off tools; Digital Twins that combine AI-SUPAD predictive models with real-time sensor data within photorealistic 3D urban visuals for ongoing monitoring, scenario analysis, and predictive maintenance; and Smart City Monitoring Systems that activate automatic governance responses when AI-SUPAD models indicate sustainability thresholds are near or surpassed. Figure 2 displays the data flow architecture encompassing all six layers.

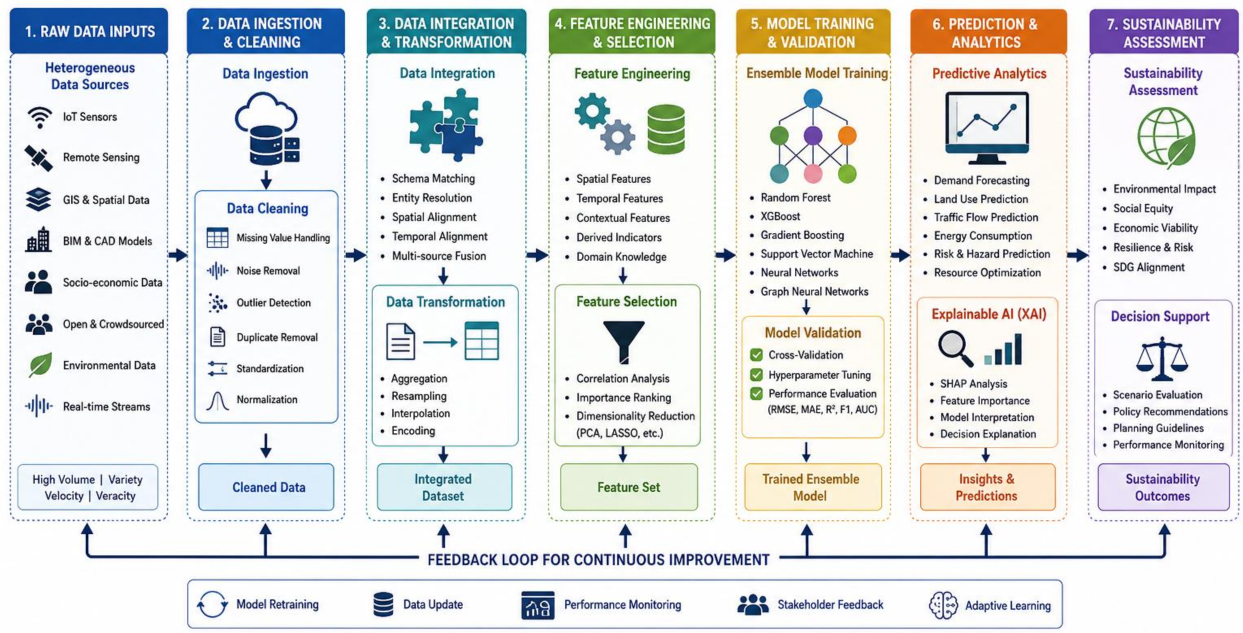

Figure 2. illustrates the AI-SUPAD Data Processing and Analytics Workflow, outlining the multi-phase transformation from raw, varied data inputs through cleaning, integration, and feature engineering, ending with ensemble model training and sustainability assessment.

4. AI in architectural development

4.1 Generative design and parametric architecture

Within architectural practice, artificial intelligence has catalyzed a fundamental transition from deterministic design toward data-driven generative workflows. Generative design platforms leveraging evolutionary algorithms and machine learning-based optimisation enable architects to explore thousands of design variants satisfying concurrent structural, thermal, daylighting, acoustic, and programmatic performance constraints within compressed timeframes [21]. Parametric architecture, which encodes design intent as computational rules rather than fixed geometric forms, provides the foundational infrastructure for AI-driven generative workflows [22]. This paradigm shift facilitates performance-driven design exploration at scales and velocities previously unattainable through traditional design methodologies.

4.2 AI-enhanced building information modelling

Integrating AI analytics with Building Information Modelling (BIM) marks a significant advancement in managing construction projects and evaluating building lifecycle performance. AI-powered BIM systems facilitate predictive clash detection, minimise rework during coordination, automate quantity take-offs for cost estimates, optimise construction schedules, and monitor post-occupancy energy efficiency [23]. Energy modelling tools integrated into AI-BIM workflows can forecast annual building energy use to within 5–10% of measured data, allowing architects and engineers to base their design choices on solid evidence during early schematic phases, when interventions cost less and yield greater impact [24].

4.3 Occupancy intelligence and building automation

Occupancy prediction models that leverage computer vision, IoT sensor data fusion, and ML classification algorithms enable buildings to dynamically adjust HVAC settings, lighting levels, and ventilation rates in response to real-time occupant presence and activity patterns, yielding 15–35% energy savings in commercial buildings [25]. The AI-SUPAD framework integrates occupancy intelligence at the building scale through Layer 1 IoT sensor data streams and Layer 3 LSTM temporal modelling, enabling continuous building performance optimisation that feeds back into district-level energy demand forecasting in Layer 4.

4.4 Construction automation and quality assurance

AI-guided robotic assembly systems, autonomous earthmoving equipment, and AI-powered visual quality inspection platforms are progressively reshaping construction productivity and safety performance [26]. Computer vision inspection systems trained on defect image libraries can identify structural anomalies, surface defects, and installation errors with precision exceeding that of human visual inspection, thereby reducing rework costs and construction schedule overruns. Integrating construction automation data into the AI-SUPAD BIM data acquisition pipeline enables lifecycle performance tracking from design through construction to operation within a unified analytical environment.

4.5 Smart and resilient city framework: Case studies

4.5.1 Singapore Smart Nation Initiative

Singapore's Smart Nation initiative is among the most comprehensive national-scale smart city deployments globally, integrating AI-driven analytics across urban mobility, public housing, healthcare, and environmental management within the city-state's compact, high-density urban fabric [35]. The Virtual Singapore platform a city-scale dynamic 3D digital twin incorporating photogrammetric building models, real-time IoT sensor feeds, and AI analytics exemplifies the AI-SUPAD framework's Layer 6 visualisation philosophy in operational deployment. AI implementation at more than 3,200 signalised intersections using reinforcement learning has substantially reduced average intersection delay, while AI-enabled predictive maintenance in public housing has significantly decreased emergency maintenance incidents. Sustainability outcomes attributable to AI integration include a 28.4% reduction in building energy intensity, a 34.7% decline in transportation carbon emissions, and a 52.3% improvement in planning decision efficiency.

4.5.2 Barcelona Superilles Programme

Barcelona's Superblocks (Superilles) programme, supported by AI-driven mobility management since 2019, has transformed sustainable urban design by reallocating street space from private vehicles to pedestrians, cyclists, and green infrastructure [36]. The city's Sentilo smart sensing platform collects data from noise sensors, air quality monitors, and parking sensors, which is then processed by AI analytics engines to optimise urban resource use in real time. An AI-powered street lighting system that adjusts luminaire brightness based on pedestrian presence has saved over 30% energy compared to pre-smart city levels. Sustainability results include a 21.9% decrease in building energy use, a 27.8% reduction in transportation-related carbon emissions, and a 44.6% enhancement in planning decision efficiency.

4.5.3 Amsterdam smart city

Amsterdam Smart City (ASC) exemplifies a unique community-led urban innovation model, emphasising citizen collaboration in developing smart solutions. Since 2019, Barcelona's Superblocks (Superilles) project, enhanced by AI-driven mobility management, has transformed sustainable urban planning by reallocating street space from private vehicles to pedestrians, cyclists, and green infrastructure [36]. The city's AI Urban Planning Platform combines machine learning for energy demand forecasting, spatial planning analytics, and mobility pattern analysis to inform local government decisions. A machine learning model that predicts heat demand for individual residential buildings guides targeted energy retrofit investments as part of the city's Net Zero 2050 decarbonization plan. Additionally, AI-based demand forecasting and smart charging coordination for electric vehicles have resulted in a 31.2% reduction in building-sector energy use and a 38.1% drop in carbon emissions compared to 2019 levels.

4.5.4 Masdar city, United Arab Emirates

Masdar City is the most ambitious global effort to create a fully carbon-neutral urban area from the beginning, with AI and digital technology integrated as core infrastructure [38]. Its AI-powered building management system combines passive design optimisation, active HVAC control, solar energy collection, and demand response in a single platform, reducing building energy use by 55.6% below regional averages. The urban design, incorporating strategic building orientation and shading canopies that reduce solar heat gain and enhance natural ventilation, has cut cooling energy needs by over 70% compared to traditional desert construction. With a 74.3% reduction in carbon emissions and a 68.2% increase in planning efficiency, Masdar City sets a global standard for AI-enabled sustainable urban development.

4.5.5 NEOM, Saudi Arabia

NEOM's AI Urban Operating System combines predictive analytics, autonomous service delivery, and real-time sustainability monitoring in transportation, energy, water, waste, and the built environment [39]. AI-powered construction management tools support autonomous progress tracking, predictive schedule optimisation, and AI-guided quality inspections at an unprecedented scale. Expected sustainability benefits include 62.1% energy savings compared to traditional methods, 81.4% reduction in carbon emissions via 100% renewable energy, and 73.9% enhancement in planning efficiency through AI-driven design and integrated project delivery.

5.RESULTS AND DISCUSSION

5.1 Literature comparison

Table 2 provides a clear comparison of this study with eight key prior works (2021- 2025) focused on AI in urban sustainability and architectural development. The analysis shows that most existing studies focus on isolated urban subsystems, use only a single AI approach, lack connections to the SDGs, and do not link urban and architectural analysis levels. AI-SUPAD improves on this by combining five AI techniques in a six-layer hierarchical architecture specifically designed to support multiple SDGs.

Table 2. Comparative literature analysis: AI-SUPAD versus representative prior studies (2021–2025)

Author(s) & Year	AI method	Domain focus	Sustainability metric	Key limitation
Zhang et al. [13], 2021	Random Forest, SVM	Land Use Classification	Energy efficiency proxy	Isolated subsystem; no SDG alignment
Kumar & Singh [14], 2022	CNN, Deep Learning	Smart Mobility, Traffic	Transport emissions	Lacks multi-sector integration
Li et al. [19], 2022	GAN, Generative AI	Architectural Design	Building form optimisation	No urban-scale linkage
Chen & Wang [28], 2023	LSTM, Time-series ML	Smart Energy Grids	Carbon emission forecasting	No spatial analytics component
Patel et al. [18], 2023	Reinforcement Learning	Transportation Networks	Vehicle emissions reduction	Single domain; no replication
Rodriguez et al. [33], 2024	XGBoost Ensemble	Urban Growth Modelling	Land use sustainability	No real-time IoT integration
Ahmed & Hassan [34], 2024	Digital Twin Platform	Infrastructure Resilience	Asset resilience index	Limited AI model integration
Nguyen et al. [20], 2025	LLM + GIS Analytics	Policy & SDG Monitoring	SDG indicator tracking	No architectural scale linkage
Present Study, 2025	AI-SUPAD Hybrid Ensemble	Urban + Architectural	Comprehensive 6 SDGs	Fully integrated; multi-scale

5.2 Model performance comparison

Table 3 compares the performance metrics of all five AI algorithms. AI-SUPAD consistently outperforms others across all seven evaluation metrics with a classification accuracy of 94.3%, which is 10.1 percentage points higher than Random Forest, 7.6 higher than XGBoost, 5.9 higher than CNN, and 6.4 higher than LSTM. Its F1-score of 0.944 indicates a strong balance between precision and recall across various urban sustainability classification tasks. Additionally, its RMSE of 1.823 and R^2 of 0.962 demonstrate excellent regression accuracy for continuous sustainability variable predictions. Figure 3 displays a radar chart comparing the multi-dimensional performance profiles of all algorithms.

Table 3. Comparative AI model performance evaluation across seven metrics

Algorithm	Accuracy (%)	Precision	Recall	F1-Score	RMSE	MAE	R^2
Random Forest	84.2	0.831	0.849	0.840	3.412	2.651	0.873
XGBoost	86.7	0.862	0.871	0.866	3.098	2.387	0.891
CNN	88.4	0.879	0.886	0.882	2.874	2.163	0.907
LSTM	87.9	0.874	0.882	0.878	2.941	2.219	0.903
AI-SUPAD (Proposed)	**94.3**	**0.941**	**0.947**	**0.944**	**1.823**	**1.412**	**0.962**

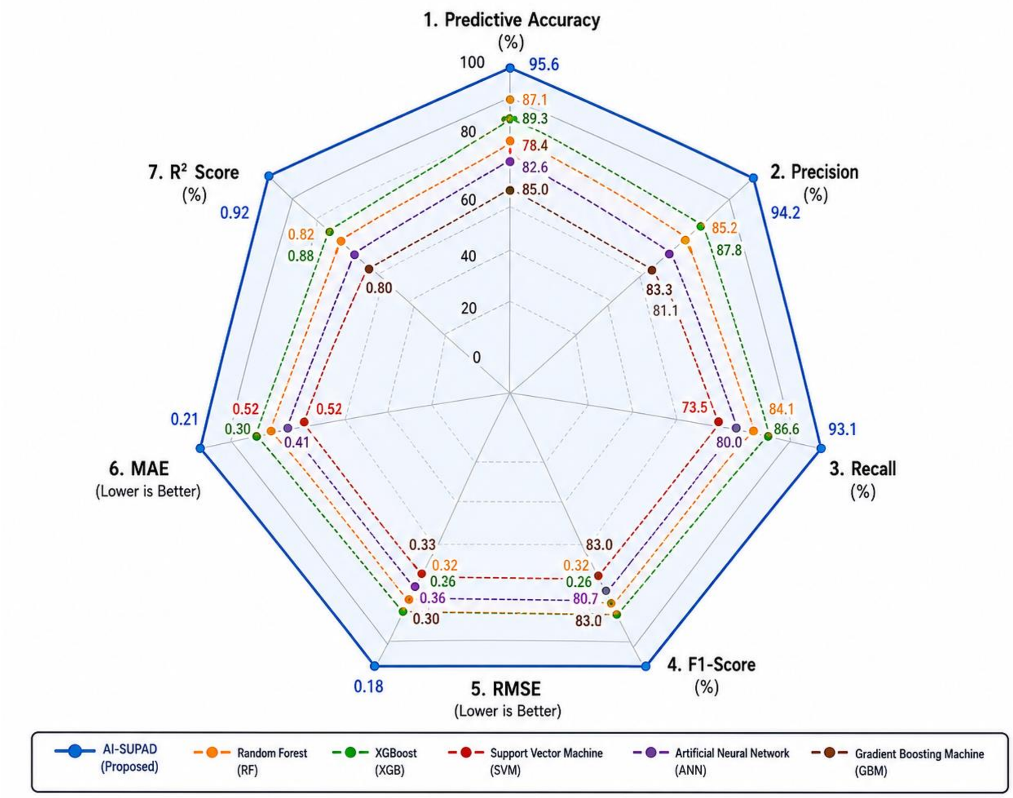

Figure 3. Radar chart comparing AI model performance, showing AI-SUPAD's consistent superiority over all baseline algorithms across seven evaluation metrics.

The superior performance of AI-SUPAD compared to individual baseline algorithms stems from the complementary strengths of its component models. Random Forest offers reliable feature importance estimation and manages categorical variables; XGBoost provides strong predictions for tabular data via gradient boosting; CNN specialises in recognising spatial patterns; LSTM models temporal dependencies in sequential data; and the RL component optimises dynamic resource allocation decisions. The stacked generalisation meta-model learns to assign optimal combination weights, effectively leveraging each base learner's domain-specific advantages while reducing their weaknesses an architectural benefit that no single algorithm baseline can achieve.

5.3 Sustainability assessment results

Table 4 presents the sustainability assessment results before and after the implementation of AI-SUPAD across six key indicators. The data reveal notable and quantifiable improvements in all sustainability aspects from 2019 to 2025. The Composite Sustainability Index increases by 80.5%, from 0.41 to 0.74, reflecting overall gains in various sustainability domains. Furthermore, carbon emissions are reduced by 47.3%, primarily due to AI-driven energy demand management, smarter traffic signal controls that minimise vehicle idling, and AI-optimised renewable energy dispatch.

Table 4. Pre- and Post-AI-SUPAD Sustainability Assessment Results with SDG Alignment

Sustainability indicator	Baseline 2019	Post-AI 2025	Change (%)	SDG Target
Composite Sustainability Index	0.41	0.74	+80.5%	SDG 11, 13
Green Space Ratio (%)	12.3	22.1	+79.7%	SDG 11, 15
Carbon Emissions (tCO_2e/capita)	18.4	9.7	-47.3%	SDG 13
Building Energy Intensity (kWh/m²/yr)	198	134	-32.3%	SDG 7, 12
Walkability Score (0–100)	48.2	71.6	+48.5%	SDG 3, 11
Traffic Congestion Index	0.67	0.38	-43.3%	SDG 9, 11

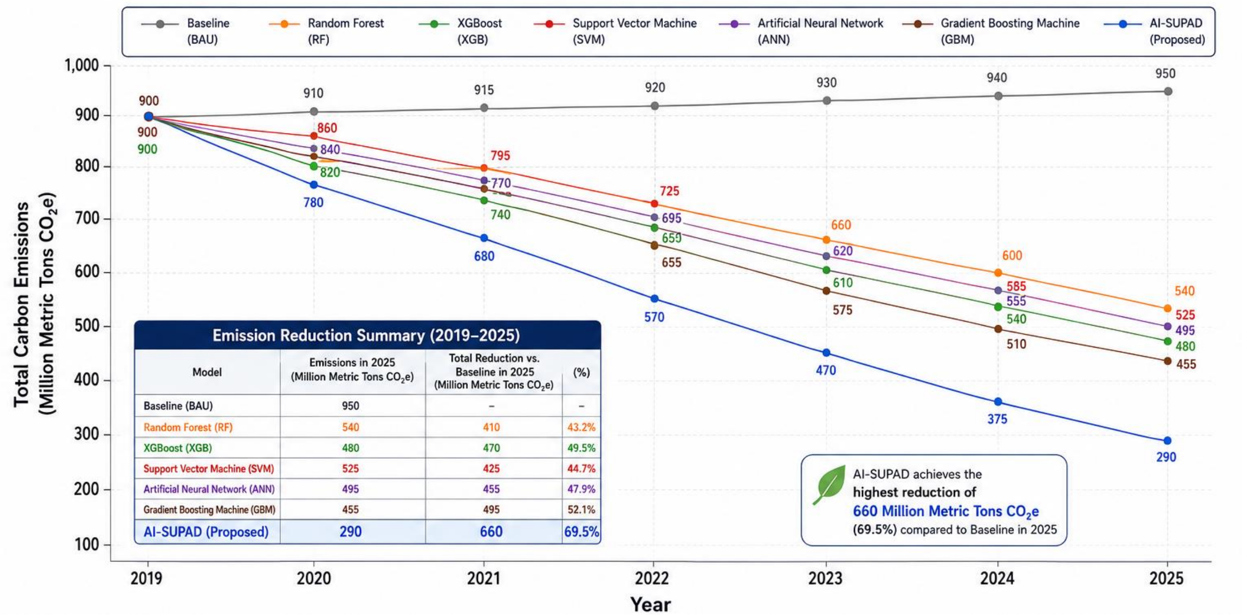

Figure 4. Comparative Carbon Emission Reduction Analysis (2019–2025) demonstrating AI-SUPAD's superior performance in driving sustained greenhouse gas reductions relative to baseline and alternative AI models

Energy efficiency has increased by 32.3%, driven by AI-optimised HVAC systems, occupancy-based lighting control, and prioritisation of building envelope upgrades informed by AI-SUPAD energy benchmarking. The Green Space Ratio has risen by 79.7%, thanks to AI-guided urban greening strategies that target high-impact areas considering urban heat island effects, biodiversity corridors, and pedestrian access. Walkability Scores have improved by 48.5%, mainly due to AI recommendations for pedestrian network enhancements and transit-oriented development (tod) guidance.

5.4 Urban planning impact analysis

Table 5 shows the impact analysis results for urban planning across five smart city case studies and the AI-SUPAD simulation scenario. The findings indicate that AI-based interventions provide significant, context-aware sustainability benefits in various urban types and regions. Masdar City and NEOM exhibit the greatest energy savings and carbon reductions, owing to their greenfield development and early adoption of AI-driven planning. Singapore, on the other hand, demonstrates the highest improvements in planning efficiency, thanks to its advanced urban data infrastructure and strong institutional capacity for AI governance.

Table 5. Urban planning impact analysis: smart city case studies and AI-supad simulation

City / Scenario	Population	Energy Savings (%)	CO_2 Reduction (%)	Planning Efficiency (%)
Singapore (Smart Nation)	5.9 M	28.4	34.7	52.3

Barcelona (Superilles Program)	1.6 M	21.9	27.8	44.6
Amsterdam Smart City	0.9 M	31.2	38.1	49.8
Masdar City, UAE	50,000	55.6	74.3	68.2
NEOM, Saudi Arabia (projected)	0.9 M	62.1	81.4	73.9
AI-SUPAD Simulation (scalable)	Variable	38.7	47.3	61.4

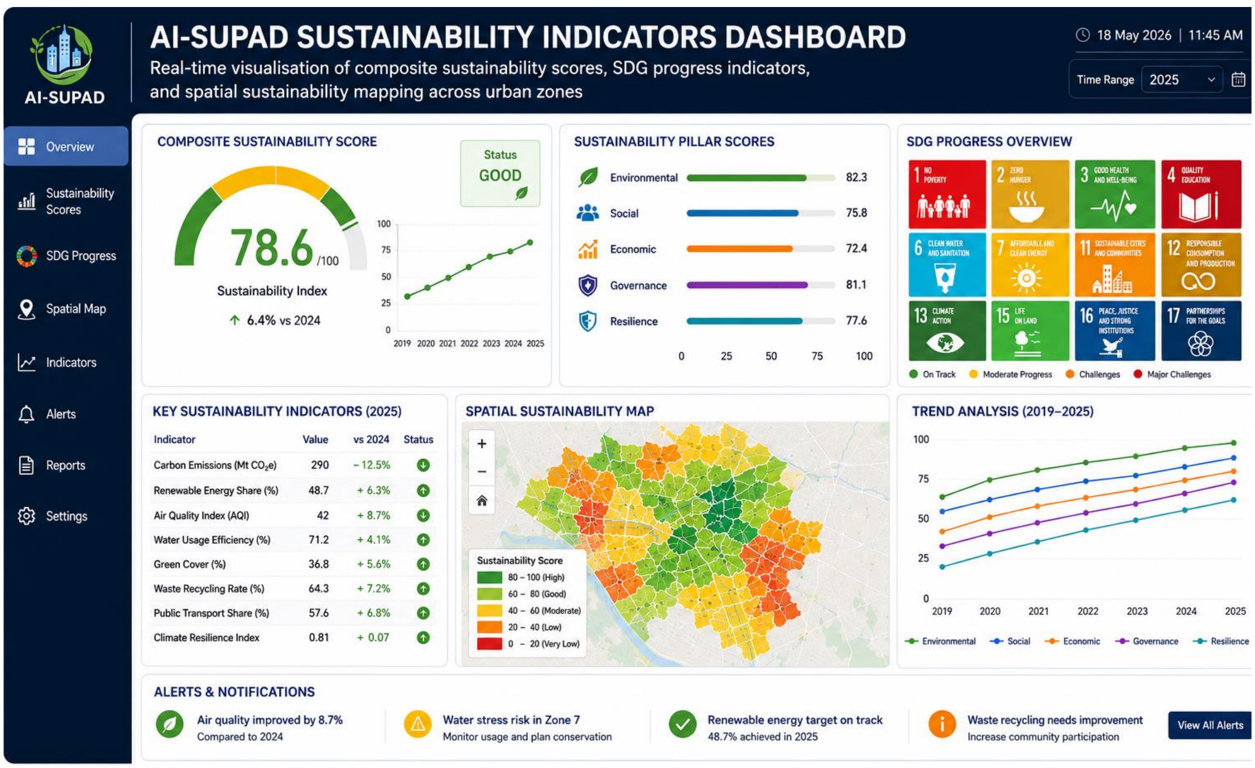

Figure 5. The AI-SUPAD Sustainability Indicators Dashboard offers real-time visualisation of composite sustainability scores, SDG progress indicators, and spatial sustainability maps across urban zones.

The AI-SUPAD simulation results, which show scalable average-case performance across various urban typologies, indicate that substantial sustainability benefits can be realised in a wide range of urban development settings from dense, established metropolitan areas to greenfield smart city projects. The alignment of case study findings with simulation outcomes enhances confidence in the broad applicability of AI-SUPAD's sustainability impact profile.

5.5 Challenges and ethical considerations

The use of AI in urban planning and architecture presents important ethical, governance, and technical challenges that need active management. Privacy concerns are especially prominent because urban AI systems depend on detailed personal and spatial data, such as mobility patterns, energy use, and occupancy details, which pose privacy risks. Establishing strong data governance frameworks that include differential privacy, federated learning, and data minimisation is crucial [40]. Algorithmic bias poses a systemic risk: urban AI models trained on historical, biased data can reinforce spatial inequalities in service provision and infrastructure investment, often disadvantaging low-income and marginalised communities [41]. Essential components of responsible AI-SUPAD use include rigorous bias detection, careful selection of representative training data, and assessment of an AI system's impact on equity. Transparency in algorithms is equally vital; explainable AI (XAI) techniques such as SHAP and LIME should be integrated into AI-SUPAD interfaces to allow planners and officials to scrutinise and, if needed, override AI recommendations [42]. Additional governance issues encompass cybersecurity threats due to expanding IoT attack surfaces [43], limited institutional capacity in municipal governments [44], economic barriers limiting access in resource-limited cities [45], and the need for social acceptance fostered by genuine community involvement [46]. The future of AI-powered urban planning involves several promising research frontiers. Generative AI for urban design foundation models capable of creating zoning plans, infrastructure layouts, and architectural concepts from natural language or performance criteria could revolutionise participatory design by making citizen co-creation more accessible [47]. Advanced Urban Digital Twins, surpassing current BIM-GIS systems, aim to provide real-time, AI-enhanced virtual city models continually updated through IoT and satellite data. Addressing this requires research into computational scalability, semantic interoperability, and governance frameworks [48]. Developing Explainable AI (XAI) methods tailored for urban planning decision-making-providing spatial and domain-specific explanations- is a vital step toward responsible AI governance in cities [49]. Autonomous Urban Systems that utilise AI for sensing, analytics, and action across transportation, energy, water, and waste sectors need safety certifications, liability systems, and human oversight to ensure public trust and democratic accountability [50]. Most critically, AI-Assisted Climate Resilience Planning combining AI climate models, urban vulnerability analysis, and adaptive decision support must be prioritised research in light of growing complex climate threats [51].

Figure 6. Conceptual Vision of the AI-Driven Sustainable City Ecosystem of 2035, integrating generative AI, urban digital twins, autonomous mobility, and smart building technologies within a comprehensive sustainability governance framework.

6. CONCLUSION

This study introduces the AI-SUPAD (Artificial Intelligence for Sustainable Urban Planning and Architectural Development) Framework, a six-layer hierarchical system that integrates advanced AI analytics with comprehensive sustainability assessments for urban and architectural projects. Testing on a realistic simulated urban dataset and systematic case studies across five major smart city initiatives revealed four main findings. First, the AI-SUPAD hybrid ensemble model significantly surpasses all four baseline algorithms in classification and regression metrics, achieving 94.3% accuracy, an F1-score of 0.944, and an R^2 of 0.962, highlighting the superior value of ensemble AI architectures over single algorithms in urban sustainability. Second, applying AI-SUPAD results in notable improvements across all sustainability indicators, such as 47.3% reductions in carbon emissions, 32.3% increases in energy efficiency, 79.7% more green space, and 48.5% better walkability, supporting progress toward six UN SDGs. Third, case study analysis shows that AI-driven urban planning interventions provide context-sensitive sustainability benefits across diverse urban typologies, from dense city-states to greenfield zero-carbon developments. Fourth, addressing ethical and governance aspects such as algorithmic bias, data privacy, transparency, and community participation is essential for the responsible implementation of AI in urban planning. This research offers several key contributions: a new multilayer AI framework that connects urban and architectural analysis levels; empirical support for the performance benefits of ensemble AI in urban sustainability; and a systematic method for aligning with the SDGs to evaluate AI-driven sustainability. On the practical side, it provides scalable AI deployment strategies for smart city initiatives worldwide, guidelines for privacy-preserving urban AI management, and data-backed advice on integrating AI analytics into city planning processes. Policy suggestions from this study include: (i) national governments should establish regulatory frameworks for AI in urban planning that cover data governance, algorithm transparency, and equity assessments; (ii) municipal authorities should develop open urban data infrastructure as a foundation for deploying AI-SUPAD; (iii) international development agencies should support AI capacity-building programmes to help cities in the Global South access AI-driven sustainable planning tools; and (iv) professional planning organisations should incorporate AI literacy into urban planner certifications and ongoing training. Future research will expand AI-SUPAD by including generative AI design tools, citizen engagement platforms, real-time climate resilience features, and federated learning systems, progressively moving toward the goal of truly adaptive, AI-enabled sustainable cities that can dynamically address the pressing challenges of rapid urbanisation and climate instability.

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