

# Practice and Application of Artificial Intelligence in Urban Decision-Making

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## 1. Introduction

With the rapid development of science and technology, artificial intelligence (AI) is gradually penetrating into all aspects of urban development, especially in the field of urban decision-making. Its application in urban planning decision-making has broad prospects [1,2]. In particular, new technologies such as big data intelligence [3,4], human-machine hybrid enhanced intelligence [5], internet group intelligence [6–8], and cross-media intelligence [9,10] will play an important role in expanding decision-making information, improving decision-making technology, enriching decision-making subjects, and strengthening decision-making feedback. When processing urban big data, artificial intelligence is mainly used for problem solving and decision analysis, including, first, how to use computer-aided design, and second, how to extract patterns and logic from the decision-making practice process [11]. It has brought new ideas and methods to urban planning, construction and management, and helped promote the practice and application of artificial intelligence in urban decision-making.

Driven by this development, this Special Issue of *Buildings* brings together 12 original papers that collectively illustrate how artificial intelligence can be applied in analysis, management, and decision-making in urban planning, spatial planning, and architectural space design. These papers cover a wide range of topics, including architectural spaces or urban park scenes in streetscapes, building scenes in remote sensing imagery, energy efficiency analysis of building carbon neutrality or urban block morphology, university outdoor spaces, highway projects, traditional garden heritage, accessible restroom design, high-density urban built environments, the price of building materials, and smart city construction technologies.

## 2. Overview of Contributions

This Special Issue primarily covers practical cases from South Korea and China, as well as specific urban case studies from Macau, Wuhan, Suzhou, Fuzhou, and Xi'an. This provides a reference for empirical analysis of AI in urban decision-making across cities of different scales and types.

Artificial intelligence has a rich and diverse technical framework, encompassing numerous methods such as machine learning, deep learning, and natural language processing. However, this Special Issue focuses on the practical needs of urban planning and architectural space, centering on the following key models and technologies:

- ResNet-50 (Residual Network)
- Multi-Scale Hybrid Dual-Attention Network (MS-HDAN)



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- Light Gradient Boosting Machine (LightGBM)
- Mask2former
- Random Forest (RF)
- Gradient Boosting Regression (GBR)
- Extreme Gradient Boosting (XGBoost)
- Artificial Neural Networks (ANNs)
- Deep Neural Networks (DNNs)
- Conditional Generative Adversarial Network (CGAN)
- Support Vector Machine (SVM)
- Real-Coded Accelerating Genetic Algorithm Projection Pursuit Model (RAGA-PPM)
- Shapley Additive Projection for Interpretability (SHAP)
- Bidirectional Encoder Representations from Transformers (BERT)
- Swin Transformer
- Non-Dominated Sorting Genetic Algorithm II (NSGA-II)
- Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN)
- Autoregressive Integrated Moving Average (ARIMA)
- Variational Mode Decomposition (VMD)
- Gated Recurrent Unit (GRU)

By employing these technologies, they offer tangible methods and examples for enhancing urban decision-making via artificial intelligence.

### 2.1. Prediction of Construction or Engineering Projects

Contribution 1 (Kim, J.-S.) developed and evaluated machine learning models using artificial neural networks (ANNs) and deep neural networks (DNNs) on a structured dataset of 150 completed national highway projects in South Korea, covering the planning and design phases. This database focuses on 19 high-impact sub-task types to reduce noise and improve prediction accuracy. This provides a reference for predicting expected life (EL) and expected life (CC) during the planning and design phases of national highway projects.

In contribution 2 (Guo et al.), an innovative forecasting model, CEEMDAN-VMD-GRU-ARIMA, was proposed. This model combines one-dimensional price series analysis with machine learning and data mining techniques to specifically predict the price of prestressed steel bars. This is crucial for effectively controlling construction project costs and managing risks.

### 2.2. Energy Efficiency Analysis

Contribution 3 (Wang et al.) developed an integrated prediction and optimization tool, combining a parametric design tool (Grasshopper), Latin Hypercube Sampling (LHS), Pearson correlation analysis, and a machine learning regression model, to investigate the impact of design parameters on heating and cooling energy consumption and photovoltaic power generation in 15 urban blocks in Wuhan. By systematically analyzing key design factors such as block building layout, orientation, proportion of low-rise buildings, and plot width, this study quantified the complicated interaction between urban form and energy performance, providing a scientific basis for optimizing urban block energy efficiency and promoting sustainable development. It also offers a scientific digital optimization framework for block planning.

Contribution 4 (Feng et al.) uses EnergyPlus and DesignBuilder for building energy simulation, applies the LightGBM model for machine learning, uses a case study of 32 buildings in Shenzhen, Hong Kong, and Guangzhou, and evaluates policies using the PEI. They embed building-scale performance analysis into the larger urban policy context

of the Greater Bay Area to gain insights into how green building activities can provide quantifiable, multi-scale benefits to China's carbon neutrality obligations.

### *2.3. Generative Design for Floor Plans*

Contribution 5 (Yan et al.) has developed an intelligent generative framework that utilizes conditional generative adversarial networks (CGANs). This paper analyzes the core characteristics of the four main spatial types of Suzhou gardens: rockery and sculpture spaces, water island spaces, pavilion and corridor spaces, and plant spaces. Based on these characteristics, a deep learning architecture is designed. Finally, the proposed model is applied to design decision generation. This paper proposes a machine learning-assisted design process, a multi-alternative comparison model, and space utilization evaluation, providing designers with efficient and multi-dimensional design decision-making.

### *2.4. Building Instance Segmentation in Remote Sensing Images*

Contribution 6 (Hu et al.) proposes a novel Multi-Scale Hybrid Dual Attention Network (MS-HDAN), which integrates a two-stream encoder, multi-scale feature extraction, and a hybrid attention mechanism. Extensive experiments on a benchmark urban building dataset demonstrate that MS-HDAN significantly outperforms existing state-of-the-art methods, particularly when dealing with densely distributed and structurally complex buildings. This framework can provide valuable support for applications such as BIM-based modeling, GIS data updates, and urban spatial monitoring. Potential users include urban planners, urban developers, and agencies involved in disaster response and land use management.

### *2.5. Street View Imagery and Spatial Analysis*

Contribution 7 (Tian et al.) used Xi'an as a case study and constructed a multidisciplinary research framework encompassing "street view imagery feature extraction, spatial heterogeneity modeling, and planning strategy optimization". Using the ResNet50 deep learning model and the ADE20K dataset, they accurately extracted ten microscale-built environment factors from tens of thousands of street view images. Combined with a high-resolution, high-quality ground-based PM 2.5 dataset from China, they employed ordinary least squares (OLS), geographically weighted regression (GWR), and multiscale geographically weighted regression (MGWR) models to systematically reveal the impact of the microscale-built environment on PM 2.5 concentrations.

Contribution 8 (Zhuang et al.) used street view images of the Fujian Agriculture and Forestry University (FAFU) campus obtained from Baidu Maps and employed a Mask2former-based image semantic segmentation method to extract landscape features. A questionnaire survey was also conducted to obtain student scores on three psychological indicators: psychological recovery, emotional enhancement, and social interaction. Subsequently, a decision tree algorithm combined with the Shapley Additive Interpretation (SHAP) mechanism was used to identify key landscape features that significantly influenced each psychological outcome and analyze their impact patterns and threshold effects.

Contribution 9 (Chen et al.) proposed a model for urban park perception and understanding based on multimodal graph-image data and a bidirectional attention mechanism. By integrating text and image data, combining a BERT-based text feature extractor, a Swin Transformer-based image feature extractor, and a bidirectional cross-attention fusion module, and applying the Shapley Additive Explanation (SHAP) method, this model can more accurately assess and identify key factors that influence visitors' emotional experiences, providing a scientific basis for urban park management and optimization.

### 2.6. Built Environment Perception and Optimization Technology

It is worth noting that with the acceleration of urbanization, the construction of smart cities has become a global focus, and machine learning technology plays a vital role in this. This also provides analytical techniques worth referring to and learning from for the urban built environment.

Contribution 10 (Luan et al.) conducted a bibliometric analysis of published research on smart cities and machine learning, using visualization techniques to reveal their spatiotemporal distribution patterns, research hotspots, and collaborative network structures. They noted that issues such as data privacy, cybersecurity, sustainable development, and intelligent transportation are becoming increasingly prominent, reflecting the dual demands of smart city development for technological innovation and green growth. This represents a key application direction and future development trend for smart city and machine learning research.

Contribution 11 (Pan et al.) quantified the intensity of human activities through Baidu heat maps, analyzed social interaction patterns using social media check-in data, and integrated built environment elements such as road network topology, three-dimensional building form, and spatial distribution of points of interest (POIs). They used a machine learning technique that combined the real-coded accelerated genetic algorithm–projection pathfinding model (RAGA-PPM) and the Shapley additive projection method (SHAP) of interpretable analysis (IPA) to explore the nonlinear mechanisms of 17 factors affecting the urban vitality of the Macau Peninsula.

Contribution 12 (Chen et al.) developed an innovative approach to accessible restroom design, integrating a Kansei Engineering (KE)–Rough Set Theory (RST)–Support Vector Machine (SVM) workflow to prioritize both inclusivity and sustainability for people with disabilities. They identified nine core emotional descriptors of accessible restroom use and extracted three representative emotional dimensions using factor analysis and clustering. Morphological analysis and RST simplification were then used to refine eight design features into six key elements. This repeatable, data-driven approach significantly benefits the alignment of emotional and functional goals in inclusive restroom design and can be expanded to other accessible facilities.

## 3. Outlook

This Special Issue presents 12 achievements in artificial intelligence and urban decision-making, which are expected to promote further developments in the fields of urban planning and architectural space and inspire future research.

In the future, the application of AI in urban planning and architectural space will continue to deeply integrate multi-source data and intelligent algorithms to create more accurate urban simulation and decision-making systems. From macro-level urban optimization to micro-level architectural space design, AI can more efficiently balance functionality, aesthetics, and resource utilization, helping to build smarter, more inclusive, and more sustainable cities, creating more habitable living and working spaces for people.

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