

Practice and Application of Artificial Intelligence in the Built Environment

Junming Chen ^{1,*} , Yile Chen ^{1,*}  and Yanyan Liang ^{2,*} 

¹ Faculty of Humanities and Arts, Macau University of Science and Technology, Avenida Wai Long, Tapai, Macau 999078, China; jmchen@must.edu.mo

² Faculty of Innovation Engineering, Macau University of Science and Technology, Avenida Wai Long, Tapai, Macau 999078, China

* Correspondence: chenyle@must.edu.mo (Y.C.); yyliang@must.edu.mo (Y.L.)

1. Introduction

With the rapid development of science and technology, the integration of artificial intelligence into the entire life cycle of the built environment is accelerating, demonstrating a broad range of potential applications in planning evaluation, design simulation, construction management, and operation and maintenance [1,2]. As a complex system, the built environment has diverse data sources spanning a large range of scales, including near-ground spatial observation data, such as street view images, as well as regional-scale information, such as remote sensing images [3–7]. On this basis, improving edge computing and smart city security governance frameworks, alongside research on energy consumption prediction, interpretable modeling, and digital twins, makes real-time risk identification, performance diagnosis, and decision feedback in the built environment increasingly feasible [8–13]. At the same time, generative artificial intelligence and multimodal large models are driving the exploration of solutions from evaluation to simulation, providing new methodological paths for built environment auditing and spatial governance [14,15].

Driven by the aforementioned trends, this Special Issue of *Buildings* includes 15 papers focusing on key aspects and processes of the built environment, including research on urban perception supported by street view images and interpretable learning, the interpretable assessment of street quality through a street view–remote sensing fusion, a path identification of public open space satisfaction among elderly visitors in World Heritage city centers, an interpretable threshold analysis of environmental safety perception for elderly residents in pocket parks, the identification and configuration optimization of campus landscape elements, the optimization of campus functional zoning considering the differences between “students and visitors”, interpretable AI-driven campus building safety assessment and design feedback, heating load prediction for residential buildings, residential unit generation based on multi-relation graph attention, the extraction and updating of facade features in historic districts, an AIGC-LoRA pre-generation and collaborative evaluation framework for updating facades of historic buildings, a modular AI workflow for building facade style transfers, a review of the progress and cutting-edge trends in generative AI research, and a systematic review of the knowledge structure of intelligent building operation and maintenance research.

2. Overview of Contributions

This Special Issue brings together the research of scholars from South Korea, Japan, New Zealand, Malaysia, the UK, and China, primarily covering real-world case studies from South Korea and China, including specific urban studies in Seoul, Guangzhou,



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Zhengzhou, Tianjin, and Shantou. These studies encompass both data-driven urban perceptions and street quality assessments centered on street view/remote sensing (e.g., Zhengzhou and Tianjin) and interpretable analyses of age-friendly public spaces (e.g., Tapgol Park in Seoul). This collection provides a reusable methodological framework, as well as case studies for the empirical analysis of AI-assisted evaluation, optimization, and renewal decisions in built environments at different scales.

The methodological framework for artificial intelligence is becoming increasingly sophisticated, covering a wide range of technical approaches from traditional machine learning to deep learning, computer vision, and generative modeling. This Special Issue focuses on application scenarios within the built environment, highlighting the following key models and technical pathways:

- Semantic segmentation and scene parsing (for street view/campus landscape element recognition).
- Object detection (for campus/building safety risk identification).
- Decision trees.
- Light GBM (Optical Gradient Boosting Machine).
- Random forest (RF).
- Geographically weighted random forest (GWRF).
- Elastic net regression.
- Generalized additive model (GAM).
- Shapley interpretable analysis (SHAP) and partial dependency analysis (PDP).
- Generative adversarial networks and conditional generation (GANs/CGANs, such as pix2pix-like frameworks).
- Efficient LoRA parameter fine-tuning (for style consistency and controllable generation for AIGC).
- Multi-relationship graph attention and WGAN generation (graph attention/RWGAN-like methods for apartment type generation).
- Convolutional long short-term memory networks (ConvLSTM) and attention modules (such as channel/temporal attention).
- Configuration analysis (fsQCA for multi-element combination mechanism identification).
- Bibliometrics and Knowledge Graph Analysis (for outlining the research trajectory of operational and generative AI).

By employing these technologies, the authors of this Special Issue offer tangible methods and examples for enhancing urban decision-making using artificial intelligence.

2.1. Urban Street Perception and Street Quality Assessment

In Contribution 1 (Zhang et al.), the authors construct an urban perception analysis framework integrating street view images and interpretable machine learning. Using Zhengzhou as a case study, they extract street visual elements based on deep learning technology and systematically analyze the multi-dimensional urban perception formation mechanism using a LightGBM model and the SHAP method. This provides data evidence for refined urban cognition and spatial governance.

In Contribution 2 (Yuan et al.), the authors use the major urban areas of Tianjin as a case study, combining street view images with remote sensing images to construct point-scale environmental indicators. They then conduct interpretable evaluations of multi-dimensional perception results, including comfort, aesthetics, perceived green space, perceived summer heat, and willingness to stay in a location, using elastic network logistic regression, a generalized additive model with logical links, and Shapley addition, providing quantitative references for street renewal and the improvement of environmental quality.

2.2. Age-Friendly Public Spaces and Safety Perception

Contribution 3 (Wu et al.) focuses on environmental safety issues related to elderly visitors in urban pocket parks in China, quantifying influencing factors by combining panoramic semantic segmentation and interpretable modeling (including SHAP and PDP). The authors highlight the positive effects of pedestrian space and moderate pedestrian activity on safety perception, as well as the significant negative impact of vehicular elements, providing actionable directions for environmental elements in micro-renewal.

In Contribution 4 (Wu et al.), the authors use Tapgol Park in central Seoul as an example, drawing on 477 valid questionnaires collected in and around the park. They use decision tree methods to identify the key paths and hierarchical logic of low-income elderly residents' satisfaction with open spaces, providing interpretive evidence for the governance of age-friendly public spaces in high-density historical urban areas.

The authors of Contribution 5 (Yang et al.) select 149 public spaces in the Yuexiu District, Guangzhou, and use Baidu heatmap data and a geographically weighted random forest (GWRf) model to analyze the impact of the built environment under four temporal scenarios. They find a significant spatiotemporal heterogeneity—building density is more important at night, while residential density is more important during the day, especially on weekends.

2.3. Campus Space Optimization and Campus Building Safety Assessment

In Contribution 6 (Zhuang et al.), the authors address the optimization of landscape composition on university campuses. By combining semantic segmentation, interpretable machine learning, and configuration analysis (fsQCA), they reveal how the combination of landscape elements collectively shapes perceptions of safety, comfort, and belonging, providing a method for configurational optimization of the campus environment.

Contribution 7 (Zhuang et al.) further focuses on the perceptual differences between students and visitors in open campuses. The authors utilize landscape element identification and enhanced decision tree (SHAP) methods to identify key factors and their threshold effects, and use this to divide campus functional zones, providing more targeted evidence for campus spatial governance.

The authors of Contribution 8 (Hou et al.) propose a YOLOv11-Safe interpretable AI framework for identifying and assessing campus building safety risks. This framework translates identification results into feedback suggestions for design optimization, demonstrating an engineering-oriented implementation path of “detection–assessment–optimization”.

2.4. Residential Space Generation and Residential Building Load Forecasting

In Contribution 9 (Ye et al.), the authors propose the Graph-RWGAN method, which characterizes the complex relationships between rooms based on a multi-relationship graph attention mechanism. It achieves an automatic generation of residential unit types through iterative generation and global consistency constraints, demonstrating a strong adaptability and flexible generation under weak constraints and diverse layouts. This provides a technical route for controllable space generation and rapid solution derivation.

The authors of Contribution 10 (Zhang et al.) propose a ConvLSTM-DyT-CBAM(T) hybrid framework, replacing the traditional batch normalization layer with a dynamic Tanh (DyT) activation function. The framework utilizes multi-scale time-series data to predict heating loads in residential buildings and enhances the response to sudden load peaks, serving such functions as operation control and energy-saving optimization.

2.5. Historic Districts and Building Facade Renovation and Style Relocation

Contribution 11 (Yan et al.) addresses the issues of facade degradation and the efficiency of traditional restoration methods in the Shantou Xiaogongyuan historical district. Based on the pix2pix model, the authors develop an intelligent facade generation system and propose a facade renewal method integrating computer vision and generative design, significantly improving design efficiency and providing a replicable path for the AI-assisted systemic renewal of historical urban areas.

Contribution 12 (Duan et al.) discusses the challenge of balancing heritage preservation and modern adaptation in historical conservation areas. The authors propose a AIGC–LoRA framework for the virtual simulation of historical building facades “before renewal” and construct a participatory, iterative “generation–evaluation” system to balance authenticity, coordination, and feasibility. Through AIGC technology, they provide an effective solution for mitigating the risks of continued preservation in historical conservation areas.

In Contribution 13 (Xu & Qu), focusing on architectural facade style transfer, the authors construct a system that integrates Flux Redux and Flux Depth models, using the node-based visual deep learning platform ComfyUI to build a modular AI workflow. By introducing a deep style collaboration process based on node-based platforms such as ComfyUI, the authors provide a reference for reusable and composable workflows in design practice.

2.6. Overview and Knowledge Graphs: Generative AI and Intelligent Operations

The authors of Contribution 14 (Yang et al.) systematically organize and analyze research literature related to use of generative artificial intelligence in architectural design from the Web of Science database, published between 2005 and 2025, using the CiteSpace visualization tool. This analysis outlines the research progress and cutting-edge trends of generative AI in architectural design, providing a general framework for the problem domain, methodological clues, and future directions of “generative design.”

In Contribution 15 (Zheng et al.), the authors retrieve 423 publications related to AI-enabled building maintenance from the Web of Science Core Collections, covering the period from 2000 to 2025. Using tools such as bibliometrix v5.0.1 and VOSviewer (v1.6.20), they conduct a systematic bibliometric and scientometric analysis, summarizing the current status and evolutionary hotspots of intelligent building operation and maintenance research. They emphasize that research hotspots are shifting from passive monitoring to proactive prediction and further toward system-level intelligent decision-making and multi-technology integration.

3. Outlook

This Special Issue compiles 15 research articles on artificial intelligence (AI) and its empowerment of the built environment field, and the work presented here will further promote the development of urban and architectural space research and practice and inspire additional related studies. In the future, applications of AI in the built environment field will continue to integrate multi-source data and intelligent algorithms to build more interpretable and transferable assessment and decision-making systems. From optimizing the quality of streets and public spaces to the renewal and generation of campuses and historical buildings, and furthermore to the prediction of residential operation and building operation and maintenance, AI will effectively support the improvement of spatial quality and the optimization of resource efficiency, helping to create a smarter, safer, more inclusive, and more sustainable built environment.

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