

An Automated Building Facade Renovation Design Framework Based on Explainable AI

Yiying Wang*

School of Architecture, Southwest Jiaotong University, Chengdu, Sichuan, 610000, China

**Corresponding author: Yiying Wang*, E - mail: wyiying792@gmail.com, ORCID:0009-0006-8325-8286*

Abstract

Facade retrofitting is a critical component of urban development, yet current practices suffer from inefficiency and strong stylistic subjectivity. To address these challenges, this study proposes and validates a novel intelligent design framework fully integrated into the SketchUp platform. This framework automates the identification and parametric reconstruction of facade geometric elements through Ruby scripting while innovatively integrating an explainable artificial intelligence (XAI)-based style recommendation engine. The core innovation lies in employing decision tree algorithms to analyze quantifiable architectural features—such as window-to-wall ratios, component types, and symmetry—thereby providing transparent, logic-based quantitative adaptation recommendations for diverse styles, including Neoclassical, Modern Minimalist, and New Chinese styles. The results demonstrate that this approach not only significantly enhances modeling efficiency but also improves the overall accuracy of style recommendations. Crucially, by translating AI’s “black box” decision-making process into clear “rules comprehensible to designers”, this research substantially strengthens human–machine collaboration. Transforms AI’s “black box” decision-making into clear, designer-understandable “if-then” rules, significantly enhancing human–machine collaboration. This not only provides innovative technical support for historic district preservation and sustainable urban renewal but also explores a trustworthy localized design solution that integrates “identification-analysis-recommendation-generation.” It holds broad application value in architectural design and engineering management.

Keywords

building information modeling, parametric design, explainable artificial intelligence (XAI); facade renovation, SketchUp Ruby, urban renewal

1. Introduction

1.1 Background: Urgency, challenges, and AI-driven design shifts in urban renewal

As the core carriers of the urban landscape and the physical interfaces of cultural memory, the renewal and transformation of building facades are crucial for maintaining urban continuity, enhancing spatial quality, and achieving sustainable development. Against the backdrop of deepening global urbanization, many existing buildings face issues of functional obsolescence and aesthetic decline, making facade renovation a key component of the urban renewal agenda. However, traditional facade renovation processes rely heavily on designers’ individual experience and manual operations, exposing numerous bottlenecks. First, manual modeling is cumbersome and time-consuming, severely limiting design iteration efficiency. Second, stylistic decisions often rely on designers’ subjective judgments, lacking objective and quantifiable foundations. This

can result in renovation proposals that fail to align with the cultural texture of the surrounding environment, making it difficult to ensure design consistency and regional appropriateness. To address these challenges, artificial intelligence technologies are increasingly being integrated into architectural generative design, demonstrating considerable application potential. The introduction of methods such as deep learning is advancing the automation and intelligence of architectural facade style recognition, generation, and optimization.

For example, generative approaches achieve efficient and controllable solutions for village plan generation through the deep integration of generative adversarial networks (GANs) with parametric techniques. However, existing AI-assisted design methods still face major bottlenecks: most generative models remain poorly integrated into practical design environments, and the “analysis” and “generation” phases often operate in isolation, limiting substantial improvements in design efficiency. More critically, mainstream AI models (such as deep neural networks) typically exhibit “black box” characteristics. AI decisions may harbor undesirable biases, struggle to meet legal requirements, and remain deficient in value assessment and perceptual judgment². This makes it difficult for designers to intervene in and guide the generation logic, resulting in limited alignment between generated solutions and design intent. This hinders the scalable application of AI technology in high-quality urban renewal. Consequently, current urban renewal practices urgently require AI design methodologies that integrate automated generation capabilities with high controllability and interpretability. Such approaches must ensure that generated outcomes align with local cultural contexts and designers’ rational judgments while enhancing design efficiency. This enables multifaceted improvements in facade transformation-including stylistic consistency, environmental adaptability, and cultural continuity.

1.2 Research Contribution: An Integrated, Explainable AI Framework

To address the aforementioned research gap, this study’s core contribution lies in proposing, developing, and validating an innovative framework fully integrated within the SketchUp design environment, grounded in explainable artificial intelligence (XAI). By leveraging the flexibility of Ruby scripting, this work directly embeds lightweight AI models (e.g., decision trees) into SketchUp, creating a truly automated tool that closes the loop of “identify-analyze-recommend-generate” operations. This addresses existing research gaps in terms of integration and practical application. This research does not pursue ultimate model complexity but prioritizes “explainability” as a primary design principle. Through careful model selection, AI can be transformed from an opaque “black box” into a transparent and trustworthy design assistant.

The specific objectives are to design, implement, and evaluate an automated tool that seamlessly integrates the entire “identify-analyze-recommend-generate” process. This tool automatically analyzes existing building facade 3D models, extracts key quantitative features, recommends the most suitable renovation styles via an explainable AI engine, clearly displays the recommendation logic to designers, and finally drives parametric scripts to automatically update and generate facade models upon user confirmation.

1.3 Paper Structure

This paper is organized as follows: Section 2 reviews architectural automated modeling, AI applications in style analysis, and the current state of explainable AI research in design. Section 3 details the proposed integrated XAI framework’s system architecture, key technical modules (including facade feature engineering, the XAI recommendation engine, and the automated modeling engine), and performance evaluation protocols. Section 4 presents the experimental results and demonstrates the framework’s effectiveness and explainability advantages through a specific case study. Finally, Section 5 summarizes the research and outlines future directions.

The experimental results demonstrate the framework’s effectiveness and interpretability advantages through a specific case study. Finally, Section 5 summarizes the research and outlines future development directions.

2. Related Research

2.1 Parametric Automation in Architectural Modeling

Parametric design has emerged as a pivotal paradigm in architectural digitalization. Defining and controlling geometry through algorithms and rules substantially enhances design efficiency and the capacity to generate complex forms. In mainstream 3D modeling software such as SketchUp, scripting via provided application programming interfaces (APIs)-such as the Ruby API-constitutes a core technical approach for achieving design automation. Research has demonstrated that scripting enables programmatic access and manipulation of model entities, automating repetitive tasks such as standardized component layout, parameter adjustment, and material substitution, thereby significantly reducing the number of modeling cycles. These efforts lay a solid technical foundation for the “automatic generation” module in this study, demonstrating the feasibility of constructing complex automated workflows within the SketchUp environment.

2.2 Application of AI in Architectural Style Analysis and Generation

Advances in artificial intelligence, particularly in computer vision, have opened new avenues for quantifying architectural styles and generating innovative designs. On the one hand, models based on convolutional neural networks (CNNs), for instance, have achieved strong performance in architectural style classification because of their robust feature extraction capabilities. On the other hand, generative adversarial networks (GANs) and their variants (e.g., Pix2Pix, CycleGAN) are widely applied in architectural “style transfer” and proposal generation. They can learn stylistic patterns from large image datasets and generate novel facade designs with specific aesthetic characteristics on the basis of input conditions (e.g., sketches, semantic segmentation maps).

However, current AI in architectural design tends to pursue model complexity and enhanced generative capabilities, inadvertently exacerbating the aforementioned “black box” issue. While complex deep learning models possess formidable functionality, their decision-making processes remain nearly entirely opaque to those of ordinary designers. This characteristic of “knowing the outcome but not the reasoning” makes it difficult for designers to establish genuine trust in AI outputs and prevents their integration into design processes requiring rigorous logical justification. The pursuit of pushing model performance to its limits stands in stark contrast to the urgent need for controllability and understandability in design practice. This creates significant room for development in research directions focused on human-AI collaboration and the prioritization of decision transparency.

2.3 Necessity of Explainable AI (XAI) in Generative Design

The rise of explainable artificial intelligence (XAI) addresses the “black box” issue inherent in AI technologies. The core objective of XAI is to develop a suite of techniques and methodologies that enable humans to comprehend AI models’ predictions and decision-making processes. In architectural design, the “rationality” and “defensibility” of design decisions are paramount. Designers must clearly articulate their design intent and logical basis to clients, regulatory bodies, and the public. AI tools incapable of explaining their recommendations-regardless of how “intelligent” their outputs appear-face significant barriers to full acceptance within professional design domains.

In this context, distinguishing between “Generative Design” and “Generative AI” is essential. The former typically refers to an iterative process based on predefined rules, constraints, and optimization goals set by designers, yielding predictable and traceable outcomes. The latter, however, relies more heavily on statistical patterns learned from massive datasets, resulting in a generative process characterized by inherent randomness and unpredictability. The innovation of this research lies in its ingenious integration of both approaches: employing an explainable generative AI model for high-level stylistic “recommendation,” then using this recommendation as input to drive a deterministic, rule-based generative design process (i.e., parametric modeling).

In summary, this research aims to bridge the gap in existing studies-where an excessive pursuit of model complexity has led to the neglect of user comprehension and trust-by introducing the concept of XAI. It provides architects with a computational design assistance tool that is both intelligent and efficient yet transparent and trustworthy.

3. Methodology: Integrated XAI-Driven Design Framework

The proposed framework is a closed-loop system seamlessly integrated within the SketchUp environment. Its core workflow is designed as four tightly interconnected phases, aiming to achieve full automation and intelligence from status analysis to scheme generation. Figure 1 illustrates the system's overall architecture.

1. Facade Analysis & Feature Extraction: Facade analysis employs deep learning methods. Specifically, the Mask R-CNN model can perform instance segmentation on user-provided facade images. This model identifies and precisely segments various facade components, such as windows, doors, balconies, roofs, decorative moldings, etc.

Each segmented element receives a category label alongside a precise pixel mask. The system subsequently extracts both geometric features (dimensions, proportions, relative positioning) and nongeometric features (material, color, texture) from these segmented elements. For example, when a window's mask is analyzed, its aspect ratio and opening ratio are calculated; when material pixel values are examined, roughness or reflectivity is quantified. These features are consolidated into a high-dimensional vector, which serves as input for subsequent style recommendation.

2. XAI-Style recommendation (XAI-Style-Recommendation): The style recommendation system is powered by a hybrid recommendation algorithm based on deep learning. It combines the strengths of content-based recommendation and collaborative filtering.

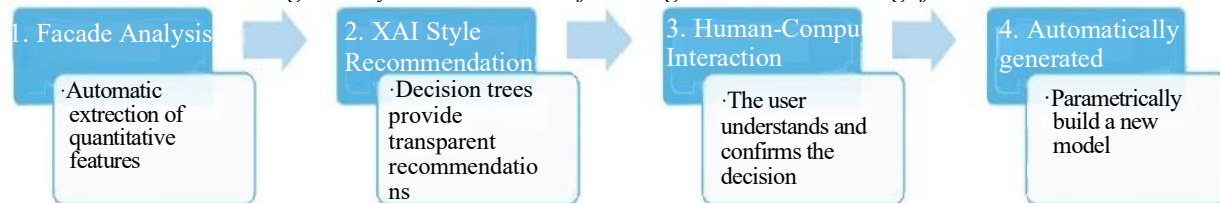
(1) The content recommendation component first feeds feature vectors extracted from facade analysis into a convolutional neural network (CNN). This network is pretrained on facade data across diverse architectural styles, enabling it to learn and recognize key visual patterns of different styles. It matches feature vectors against predefined style labels (e.g., modern, classical, or art deco) and outputs preliminary style confidence scores.

(2) The collaborative filtering component optimizes recommendations by analyzing historical user selection behavior. When a user confirms or modifies a recommended style, the system records this action. If multiple users select the same style for similar facade features, the system learns this as a strong association. For new users with comparable facade characteristics, collaborative filtering provides more precise supplementary recommendations—even those capturing nuances missed by the CNN model. The final recommendation result is a composite score calculated by weighting the outputs of both algorithms.

(3) Next, user engagement (human-machine interaction and decision confirmation), where the system's key innovation lies, is considered. It not only presents recommendation results but also clearly and intuitively reveals the decision logic behind these recommendations (e.g., through “if-then” rule chains). Users can evaluate the rationale of recommendations on the basis of these explanations and make final decisions.

(4) Finally, automated parametric generation occurs. When the user confirms their chosen style, this instruction triggers the backend parametric modeling engine. Ruby scripts automatically execute a series of modeling operations based on the design rule library corresponding to the selected style—such as replacing door and window components, applying new materials, and generating decorative lines—ultimately constructing a new 3D facade model within minutes.

Figure 1: System architecture of the integrated XAI-driven design framework



3.1 Facade Analysis and Quantifiable Feature Engineering

To enable AI models to “understand” architectural facades, complex building forms must first be converted into machine-readable numerical data. This process, termed “feature engineering,” is fundamental to AI model

performance and constitutes a significant core task of this research. On the basis of established architectural typology theory⁴, a systematic facade analysis framework was developed, along with corresponding Ruby scripts, to automatically extract the following key features from SketchUp models.

Table 1: *Quantifiable features for architectural style analysis*

Feature Category	Measurement Metric	Definition and Calculation Method (via SketchUp Ruby API)	Architectural Style Association
1. Composition and Volume	Window-to-Wall Ratio (WWR)	Ratio of total window area to total exterior wall The ratio of the total window area to the total solid surface area of the exterior walls. By iterating through all component instances labeled as “window,” accumulating their surface areas and dividing by the total surface area of components labeled as “wall.”	A high WWR (e.g., >0.6) is a defining characteristic of modernist architecture; conversely, a low WWR is common in traditional or classical styles.
	Symmetry Index	A score between 0 and 1 measuring the degree of geometric symmetry along the central vertical axis of a facade. It is calculated by mirroring the geometry of one side of the facade onto the other, then determining the ratio of overlapping volume to total volume.	High symmetry serves as a core organizing principle in Neoclassical and New Chinese styles ²¹ .
	Horizontal/Vertical Emphasis	Ratio of the total length of primary horizontal lines (e.g., eaves, string courses) Total length of primary horizontal lines (e.g., eaves, string courses) divided by total length of primary vertical lines (e.g., pilasters, vertical window frames)	Strong horizontal lines are one of the hallmarks of modernism ³ ; verticality is more prominent in Gothic or Art Deco styles.
2. Element Density and Opening Distribution	Element Density	The number of discrete elements (doors, windows, balconies, etc.) per 100 square meters of facade surface area..	High-density, small-scale openings may suggest traditional styles; low-density, large-area openings point toward modernism ¹² .
	Average window aspect ratio	The average ratio of height to width for all window instances	Slender vertical windows and expansive horizontal panoramic windows serve as powerful indicators for distinguishing different architectural styles.
3. Material and Decoration	Material Complexity	The number of different materials used on the facade	The mixed use of multiple materials is a technique employed in certain contemporary modern styles technique, while the extensive use of a single material is also a defining characteristic of minimalist styles.
	Decorative Index	A proxy metric for the complexity of decorative elements (such as intricate moldings or carved brackets) in a model, approximated by calculating the total number of surface polygons (Polygon) count.	A high index indicates elaborate decorative style (e.g., Neoclassical); a low index indicates a minimalist tendency.

The construction process of Table 1 is itself a rigorous research effort. This ensures that the input to the AI model is based on profound architectural knowledge rather than arbitrarily selected data, thereby providing a solid theoretical foundation for the model’s accuracy and interpretability.

3.2 Explainable AI Style Recommendation Engine

3.2.1 Theoretical Basis for Model Selection: Commitment to Explainability

This study explicitly prioritizes “explainability” over model performance, leading to the selection of the decision tree algorithm as the core of the style recommendation engine. This choice directly embodies the XAI principle, offering the following advantages:

(1) High interpretability: The inherent logic of decision trees can be intuitively visualized as tree-like flowcharts, where each decision node corresponds to an “if-then-else” rule. This structure closely mirrors human decision-making processes, enabling architects without data science backgrounds to easily understand why the model proposes specific recommendations. This fundamentally resolves the “black box” issue of AI.

(2) High computational efficiency. As lightweight models, decision trees require minimal computational resources for training and prediction. This enables seamless integration into local software environments such as SketchUp without relying on cloud APIs or high-performance hardware, ensuring responsive tool performance and ease of use.

(3) The third point is its native handling of mixed data. The decision tree algorithm can naturally process both numerical data (e.g., window-to-wall ratio) and categorical data (e.g., primary material type) without complex preprocessing, simplifying the development workflow.

3.2.2 Style rule library definition

This represents another critical step reflecting the research effort. First, multiple classic architectural styles were deconstructed and transformed into a “digital rule library” composed of the quantified features listed in Table 1. For example:

(1) Modern Minimalist Style Rule Library: Its feature space is defined by a high window-to-wall ratio (>0.6), low symmetry index, strong horizontal emphasis, low ornamentation index, and low-complexity material panels composed of concrete, glass, metal, etc.

(2) New Chinese style rule library: Its feature space is defined by a high symmetry index, the use of symbolic elements such as courtyards or latticework, specific materials such as blue bricks and dark wood, and window lattice forms with unique height–width ratios.

3.2.3 How AI Decision-Making Drives Localized Automation

This research uniquely integrates AI’s “brain” (decision tree models) with SketchUp’s “hand” (Ruby scripts), enabling localized and seamless design processes. Decisions are made on the basis of features extracted by an XAI-style recommendation engine. These decisions—such as labels indicating a “neoclassical” style—are explained to designers through explicit “if-then” rules. Crucially, these labels are not exported to external software but serve as input parameters that directly trigger subsequent automation scripts within SketchUp. This design eliminates frequent switching between analysis and modeling environments in traditional workflows, resolving the “disconnected workflow” issue. It brings AI’s intelligent analysis capabilities directly into the designer’s real-time working environment, making “recommendation” and “generation” a continuous, highly integrated action. This truly achieves an operational closed loop from data-driven insights to automated model generation. This deep integration is key to the framework’s efficiency and ease of use.

3.3 Automated Parameterization Engine

This engine serves as the critical execution layer connecting AI decisions to physical modeling. Written as a Ruby script interpreter, its primary task is to accurately translate style tags—determined and output by the explainable AI engine—into input parameters that drive a series of automated SketchUp modeling commands. This mechanism ensures seamless translation of abstract AI decisions into concrete, controllable design operations. The key functional modules include the following:

1. Component Mapping and Intelligent Replacement: The script maintains an internal “style-to-component” lookup table. Upon receiving a “modern style” instruction (), it automatically retrieves components such as “Modern_Window_Component” () from a predefined library. The script then iterates through all entities in

the current model and identifies outdated components marked for replacement (e.g., all instances named “Old_Window”) and precisely replaces them with new components from the library while preserving the original transformation information such as position, rotation, and scale.

2. Automatic material application: On the basis of AI-recommended style rules, the script automatically applies new materials to specified surfaces (faces).

3. Parametric Geometry Generation: For more complex renovation tasks, the script dynamically generates new geometries on the basis of parametric rules-such as automatically creating eaves or fascia lines from wall boundaries.

3.4 Performance evaluation protocol

To scientifically and objectively validate the proposed framework, an evaluation protocol encompassing multiple dimensional metrics was designed. (Using a dataset of 200 building facades awaiting renovation as an example)

(1) Modeling efficiency:

The first metric is the time reduction percentage, which is calculated as follows:

$$\text{Time reduction} = T_{\text{manual}} - T_{\text{automated}} \times 100\%.$$

The second protocol is an evaluation process: N standardized facade renovation tasks are selected. Each task is completed manually by a skilled SketchUp designer and automatically via the framework’s script. The time required for each method was precisely recorded: T_{manual} and $T_{\text{automated}}$.

(2) Style recommendation performance:

The evaluation process involves reserving a portion (e.g., 25%) of the constructed 200-sample dataset as a “test set.” These data are excluded from model training and are specifically used to assess the model’s generalization ability when encountering “unseen” facades.

With respect to the core evaluation metrics, this paper employs confusion matrices to visualize classifier performance. The confusion matrices clearly illustrate the model’s correct and incorrect predictions across each category.

Finally, key performance metrics require the following four core classification indicators to be calculated on the basis of the confusion matrix to evaluate model performance comprehensively:

Accuracy: The proportion of correctly predicted samples out of the total number of samples, reflecting the model’s overall performance.

Precision: The proportion of samples correctly classified as belonging to a specific style among all samples predicted by the model. The formula is $\text{Precision} = (TP + FP)/TP$. High precision indicates that when the model makes a positive prediction, the result is highly reliable.

R-ecall (sensitivity): The proportion of samples that actually belong to a specific style that are correctly predicted by the model. The formula is $\text{Recall} = TP + FN/TP$. A high recall indicates that the model effectively “finds” all instances of the target style.

F1 score: The harmonic mean of precision and recall, calculated as

$$F1 = 2 \times \text{Precision} \times \text{Recall} / (\text{Precision} + \text{Recall}).$$

It provides a balanced performance metric, particularly when the number of samples across categories in a dataset is imbalanced, reflecting the model’s true capability more accurately than simple accuracy alone.

4. Results and Discussion

4.1 Case study: Interpretable design workflow practice

To demonstrate the framework’s practical value, we present a complete workflow demonstration using a typical facade renovation case study.

Initial State and Feature Extraction: Figure 2(a) shows the building facade slated for renovation, exhibiting a slightly antiquated style. Upon triggering the framework, the analysis module automatically extracts its feature vectors. For example, {Window-to-wall ratio: 0.25, symmetry index: 0.85, ornamentation index: 0.7,...

XAI Recommendations and Explanations: This feature vector is fed into a decision tree model. The model outputs a recommendation: “Neoclassical style, 93% confidence.” More importantly, the system reveals its decision-making process to the designer. The simplified logic shown in Figure 2(b) is as follows: “Since the symmetry index > 0.8 , the ornamentation index > 0.6 and the window-to-wall ratio < 0.4 , the recommended style is ‘Neoclassical’.”

User Decision & Automated Generation: This explicit explanation enables designers to comprehend and trust the AI’s suggestion. Upon designer confirmation, the parametric generation engine is activated. The script automatically executes a series of operations based on the “Neoclassical” style rulebook, such as replacing windows with arched ones, adding classical columns and eaves lines, and adjusting wall materials. The entire process takes approximately 3 minutes, resulting in the remodeled model shown in Figure 2(c), which features a unified style and rich details.

Figure 2: Case study workflow. (a) Prerenovation façade; (b) automatically generated postrenovation façade



4.2 Discussion

4.2.1 Interpretation of the Results

The quantitative results and case studies in this research jointly validate the effectiveness of the proposed framework. Significant efficiency gains demonstrate the value of automated workflows, whereas high-accuracy AI recommendation performance confirms the feasibility of data-driven decision-making. More profoundly, this study seamlessly integrates both aspects into a unified, user-friendly tool.

4.2.2 Practical Value of Explainability

The core assertion of this study is that in architectural design, the “explainability” of AI tools is equally important-if not more so-than their “accuracy.” Unlike “black-box” generative AI models that produce outputs while concealing their processes, this framework enables effective communication between humans and AI by revealing the explicit logic of decision trees. Designers are no longer passive recipients of “magically” generated outcomes but can actively comprehend, evaluate, and validate AI suggestions. This transparency significantly enhances designers’ trust in the tool, transforming AI’s role from that of a potential competitor into that of a collaborative, trustworthy intelligent assistant that fosters meaningful human-involved design processes.

4.2.3 Limitations and Future Research Directions

As an exploratory endeavour, this study has certain limitations while also opening new avenues for future research:

(1) First, regarding the expansion and dynamic learning of the style library, the current model’s training dataset only includes a limited number of architectural styles. Future work will focus on expanding the model style library by collecting and annotating more diverse data while exploring online learning or incremental learning methods to enable the model to continuously optimize and adapt to new style trends on the basis of designer feedback.

(2) Second, enhancing geometric capabilities is essential: the current feature extraction script primarily targets linear geometry. Its analytical capacity is limited for facades featuring complex surfaces or nonorthogonal forms. Future exploration could incorporate more advanced 3D model analysis techniques, such as graph neural networks (GNNs). The data-driven and representation-learning characteristics of deep neural networks enable them to extract morphological patterns from extensive existing traditional texture cases, generate texture layouts aligned with local urban aesthetics, and repair disrupted urban textures.⁵

(3) Another area for improvement lies in aesthetics and performance. Current recommendations focus primarily on aesthetics and morphological characteristics. A more ambitious future direction involves integrating building performance analysis (energy consumption, solar exposure, structural efficiency, etc.) into the recommendation engine.

This transforms the problem from single-objective style classification to a multiobjective, comprehensive performance optimization challenge. Consequently, designers will be empowered to deliver sustainable façade improvement solutions that are both aesthetically pleasing and high performing.

5. Conclusion

This study successfully developed and rigorously validated an automated facade renovation and style recommendation framework for architecture, leveraging SketchUp Ruby scripts and explainable AI. The key findings demonstrate that the framework significantly enhances the facade modeling efficiency while substantially improving the style recommendation accuracy. It achieves an intelligent closed-loop process—from feature analysis to model generation—within a single design environment.

The primary contributions of this research are twofold. First, it offers a novel approach bridging the gap between AI-driven analysis and parametric automation within mainstream design platforms, providing efficient, reliable, and user-friendly technical support for architectural heritage preservation and urban renewal. Second, of greater theoretical value, this study represents a successful application of explainable AI (XAI) principles in architectural design tool development. This demonstrates that through careful model selection and system design, intelligent yet transparent design assistance tools can be constructed, thereby enhancing trust and efficacy in human-machine collaboration.

Despite these positive outcomes, room for improvement remains in expanding the style library's breadth and enhancing complex geometric processing capabilities. Future research will focus on expanding AI model training datasets and exploring integration with more advanced analytical techniques such as graph neural networks. In the long-term, combining aesthetic recommendations with architectural performance optimization is expected to evolve into a more comprehensive decision support system. This will support sustainable urban regeneration, ultimately advancing the digitalization and intelligent transformation of architectural design and construction processes while achieving harmonious integration with cultural heritage preservation.

References

- Bo, H., Deng, L. and Wangyang, G., (2025). Preliminary exploration of architectural space creation from a typological perspective. *Urban Environment Design*, no. 2, pp. 134-138.
- Hao, H., (2024). *Exploration of Computational Methods for Clustering and Generating Urban Morphologies in Old Cities Based on Deep Neural Networks*. Master's Thesis, South China University of Technology.
- Li, J., Qin, H. and Xu, Z., (2024). Published. A study on historical buildings based on cnn: A case study of the five avenues area in Tianjin. 2024 National Symposium on Teaching and Research of Digital Architectural Technology in Architectural Departments, 2024 Kunming, China. National Steering Committee for Architectural Education, Architectural Digital Technology Teaching Working Committee, pp. 399-393.
- Ma, G. and Yang, R., (2025). The black box dilemma of AI commercial decision-making and its resolution *Journal of Beijing Union University(Humanities and Social Sciences)*, pp. 1-13.
- Zhang, Z., (2025). *Research on plan generation of villages along the inner mongolia section of the Yellow River based on generative adversarial networks*. Master's Thesis, North China University of Technology.

Funding

This research received no external funding.

Conflicts of Interest

The authors declare no conflict of interest.

Acknowledgment

This paper is an output of the science project.

Copyrights

Copyright for this article is retained by the author (s), with first publication rights granted to the journal. This is an open - access article distributed under the terms and conditions of the Creative Commons Attribution license (<http://creativecommons.org/licenses/by/4.0/>).

Appendix A: SketchUp Ruby Script Core Logic Pseudocode

```
# Retrieving the current model
model = Sketchup.active_model

# Start an operation (with undo capability)
model.start_operation("Replace Windows")

# Get all entities in the model
entities = model.entities

# Search for every instance of the "Old_Window" component among all entities
entities.each do |entity|
  if entity.is_a? (Sketchup::ComponentInstance) && entity.definition.name == "Old_Window"

    # 1. Get the position and orientation of the old window
    transformation = entity.transformation

    # 2. Remove the old window
    entity.erase!

    # 3. Find the new window component by name in the component library
    new_window_def = nil
    model.definitions.each do |def|
      if def.name == "Modern_Window_Component"
        new_window_def = def
        break
      end
    end

    # 4. Place the new window at the exact position of the old window
    if new_window_def
      entities.add_instance(new_window_def, transformation)
    end
  end
end

# End operation
model.commit_operation

# Display a prompt on the interface
UI.messagebox("Window replacement complete!")
```

(This section provides a key function pseudocode for the Ruby script used in feature extraction and parameterized generation, accompanied by detailed annotations to ensure reproducibility of the research.)