

# Research on the Application of Stable Diffusion-Based Generative AI Tools in Environmental Art Design Education

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**Abstract:** The breakthrough development of Artificial Intelligence Generated Content (AIGC) technology is reshaping the creative paradigm in the field of environmental art design. In 2023, an article on a deep learning-based model for automatic urban planning was first published in Nature Computational Science [1]. Traditional design tools are increasingly showing limitations in addressing the complexity, efficiency demands, and innovation dimensions of contemporary design needs. In contrast, generative AI tools (such as MidJourney, Stable Diffusion, etc.), through algorithm-driven creative models, demonstrate revolutionary potential in fields like architectural design, visual communication, and environmental art design [2]. These technologies can not only efficiently solve complex problems such as spatial form generation and multi-element collaborative design but also promote a paradigm shift in design thinking from "manual trial-and-error" to "intelligent evolution." In higher education, creative learning ability, as a core competency for individual lifelong development and social progress, has become an important goal in cultivating design talent [3]. This research focuses on the pedagogical innovation of generative AI in environmental art design education, using Stable Diffusion platform's Text-to-Image and Image-to-Image functionalities as the technical carriers. Through literature review, case studies, and process-based design methods, it deeply explores the application and potential for improvement of generative AI design tools in environmental art design education. Research findings indicate that generative AI provides instant visual feedback, expands the boundaries of design possibilities, and promotes human-AI collaborative innovation, bringing a technological tool revolution to environmental art design education.

**Keywords:** Stable Diffusion, Text-to-Image, Image-to-Image, Lora, ControlNet

## 1. Introduction

With the deepening promotion of sustainable development concepts in China and the growing market demand for green buildings and low-carbon design, environmental art design has become a key topic of concern for current social development and national policies. In recent years, artificial intelligence technology has shown significant application potential in fields such as landscape planning and architectural design, enabling the rapid and efficient generation and optimization of complex design schemes through AI generation tools. During this process, models based on deep learning can simulate human artistic creation, outputting artistic design patterns and spatial layouts that meet specific scene requirements. However,

practical application still faces many challenges, such as inconsistent generation quality and insufficient cultural adaptability. These are not only current bottlenecks in AI technology but also major reasons hindering its deep integration into environmental art design education [4]. In the field of environmental art design education, the choice of tools directly affects students' creative efficiency and work quality. Traditional design tools like SketchUp, Figma, and the Adobe suite, despite numerous optimizations in user experience, still have limitations. For example, some tools have complex interfaces and high learning costs; functional modules are scattered, leading to reduced work efficiency; furthermore, the level of tool intelligence is limited, making it difficult to meet the

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balance sought by students and designers between creative expression and efficiency enhancement. Existing research pays less attention to the adaptability of generative AI tools in educational settings and their impact on learning outcomes.

Generative Artificial Intelligence (Generative AI) is a technology capable of automatically generating content, with its core lying in simulating human creativity. Diffusion Models, as one of the most popular generative AI techniques in recent years, are widely used in the field of art design due to their high-quality output and flexibility. Stable Diffusion, as an open-source diffusion model framework, has become an important tool for designers exploring creative expression due to its efficiency and controllability. In recent years, with breakthroughs in deep learning technology, generative AI tools such as MidJourney and Stable Diffusion have gradually become mainstream AI tools entering the design field. These tools can simulate human creativity through algorithms, rapidly generate high-quality visual elements, and provide important auxiliary functions for designers and design students.

## 2. The Development of Generative AI Tools

The development of generative AI tools has gone through several stages, with technological paths gradually shifting from traditional statistical models to deep learning-based generative models:

1. Early Models: Based on Markov chains, Hidden Markov Models (HMM) generation methods, with limited generation capabilities.

2. GAN Era (2014-2020): Generative Adversarial Networks (GANs) significantly improved generation quality through adversarial training between a discriminator and a generator, but faced issues like mode collapse and training instability [5].

3. VAE and Flow Models: Variational Autoencoders (VAE) and Normalizing Flows generated data through probabilistic modeling, but generation quality and efficiency were still limited.

4. Rise of Diffusion Models (2020-Present): Diffusion models generate data through a reverse process of gradual denoising. Combined with stable training and high-fidelity output, they have become the current mainstream technology. Stable Diffusion (2022) significantly reduced computational costs by compressing the diffusion process into latent space, promoting the popularization of generative AI [6].

### 2.1 Core Innovations of Stable Diffusion

Stable Diffusion, open-sourced by Stability AI in collaboration with several research teams, is a generative AI tool based on the Diffusion Model, widely used in image generation tasks. Its core algorithm is the diffusion model, a technique that generates high-quality images by gradually adding noise and learning the denoising process. The core idea of the diffusion model is implemented through the following two steps:

Forward Process: Gradually adds random noise to the input clear image, eventually obtaining a completely random noise image.

Reverse Process: Trains a neural network to learn how to gradually recover the clear image from the noise.

The key to the diffusion model lies in learning the "denoising" process from noise to the target image. Through extensive training data, the model can capture the details and features in the images and reproduce this information during generation.

Its core technological breakthroughs include:

1. Latent Diffusion Model (LDM): Compresses high-resolution images into a low-dimensional latent space and performs the diffusion process in this latent space, reducing computational load (traditional diffusion models operate directly in pixel space, incurring extremely high computational costs). Uses a pre-trained Variational Autoencoder (VAE) to map between images and latent space.

2. Conditional Control Mechanisms: Achieves multi-modal controllable generation through conditional inputs such as text prompts (CLIP text encoder) and image segmentation maps. Supports fine-tuning (e.g., LoRA) and plugin extensions, adapting to different vertical domains.

3. Open Source Ecosystem: Model weights and code are completely open source, fostering a rich ecosystem of community tools (like Automatic1111's WebUI) and commercial applications (art creation, advertising design, etc.).

### 2.2 Updates and Iterations of Stable Diffusion

Stable Diffusion is an optimized version of the original diffusion model, with major improvements including:

- Enhanced Stability: Improves the quality and consistency of generated images by adjusting parameters of the diffusion process (such as the number of noise addition steps).

- Multi-modal Support: Besides image generation, Stable Diffusion also supports multiple task modes like text-to-image and image-to-image.

- **Efficient Inference:** The optimized model can complete generation tasks quickly on standard computers, reducing reliance on high-performance hardware.

### 3. Application of Generative AI Design Tools in Environmental Art Design Education

**Table 1: Common Generative AI Models in the Context of AIGC Technology**

| Model Name              | Generation Category          | AI Model Features                                                                                                                                                                                                                                                                                                                                          |
|-------------------------|------------------------------|------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| <b>Stable Diffusion</b> | <b>Image/Video/3D</b>        | <ul style="list-style-type: none"> <li>- Open-source model, supports local deployment and customization.</li> <li>- Based on Latent Diffusion Model (LDM), high computational efficiency.</li> <li>- Supports multi-modal control (text, edge detection, depth maps, etc.).</li> <li>- Highly extensible (plugins like ControlNet, LoRA, etc.).</li> </ul> |
| <b>Midjourney</b>       | <b>Image</b>                 | <ul style="list-style-type: none"> <li>- Closed-source commercial model, users interact via Discord.</li> <li>- Strong artistic stylization output (favors oil painting/sci-fi styles).</li> <li>- Excels at complex compositions and surreal scenes.</li> <li>- Does not support fine-grained control, relies on prompt optimization.</li> </ul>          |
| <b>DALL·E 3</b>         | <b>Image</b>                 | <ul style="list-style-type: none"> <li>- Text-to-image model developed by OpenAI.</li> <li>- Deeply integrated with ChatGPT, supports complex semantic understanding.</li> <li>- Generated content adheres to safety policies (automatically filters sensitive content).</li> <li>- Accessible only via API, no open-source version.</li> </ul>            |
| <b>GPT-4</b>            | <b>Text/Code/Multi-modal</b> | <ul style="list-style-type: none"> <li>- Currently the most powerful general-purpose language model.</li> <li>- Supports long text generation and complex logical reasoning.</li> <li>- Extensible to image understanding (requires integration with multi-modal interfaces).</li> <li>- Closed-source model, requires paid API calls.</li> </ul>          |

Compared to traditional design tools, the application of generative AI design tools in environmental art design education essentially combines the "infinite imagination" of AI with the "logical control" of human designers. Its value lies not only in improving design efficiency but also in expanding the possibilities of environmental narratives. In educational settings, design tools are not just

auxiliary means for teaching but also important carriers for students to cultivate creativity and practical abilities. Research indicates that the functionality and usability of tools directly affect their application effectiveness in the classroom. Students tend to prefer design tools with concise interfaces and clear functions, and believe these tools help them complete design tasks better [7]. Furthermore, the demands for design

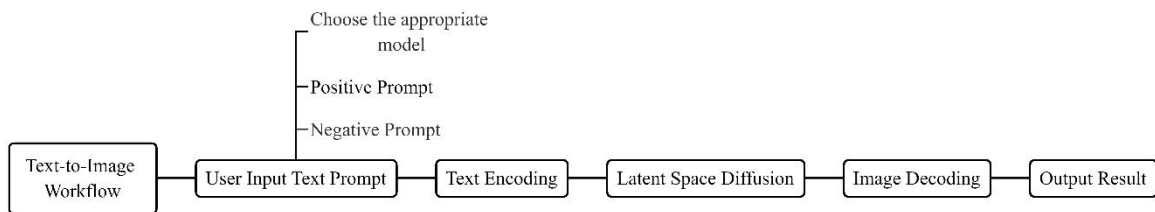
tools in educational settings have specific characteristics. On the one hand, tools need a certain degree of flexibility and extensibility to adapt to the teaching needs of different disciplines; on the other hand, the functional design of tools should focus on integration with teaching objectives, such as supporting collaborative learning and providing real-time feedback.

In environmental art design creation, the entire design process includes five stages: preliminary concept design, schematic design, design development, construction drawing preparation, and finally handover for construction documents. The preliminary concept design is the starting point of the entire workflow and also the most crucial part. Previous concept design required significant time and effort to collect spatial

intention images to determine the final direction of the scheme. Aspects like main form, design style, and functional layout all required repeated modifications and refinements to gradually perfect. Different design stages are handled by different tasks. Generative AI tools (especially Stable Diffusion) applied in the environmental art design field are thoroughly changing the traditional design workflow, demonstrating strong potential from conceptualization to scheme implementation. The following sections will illustrate its revolutionary value through application scenarios combined with specific practical examples.

### Application Scenarios and Process Innovation

#### 3.1. Preliminary Concept Design Phase: Rapidly Generate Creative Sketches, Diverge Creative Thinking



(Figure 1: Stable Diffusion Text-to-Image Workflow Diagram (Image source: Author's drawing))

- (Prompt-driven) Text-driven Design: In the initial stage of scheme design, students in environmental art design can simply describe the scheme using natural language: e.g., "modern minimalist city square, art sculpture integrated with sparse forest and grassland, sunny weather." Using Stable Diffusion, multiple versions of conceptual spatial renderings can be generated, breaking through

the efficiency bottleneck of traditional hand-drawing or 3D modeling. This significantly improves learning efficiency and the quality of output compared to traditional design tools.

( Model parameters: Base Model: UrbanDesign\_v7, Sampler: DPM++ 2M Karras, Steps: 25, VAE: vae-ft-mse-840000-ema-pruned.safetensors, CFG scale: 8)



(Figure 2: Scheme Generation Based on Prompt Description. Image source: Author's drawing.)

- Style Transfer (ip-Adapter): When a conceptual scheme has reached a preliminary model stage, Stable Diffusion's style transfer function can be used for secondary modification. By integrating a designated artist's style onto the project requiring modification, loading desired reference work images, and pairing with the ControlNet plugin to control building form,

customized style conceptual design schemes can be generated.

(Model parameters: Base Model: juggernautXL\_v9\_V9 + RDPhoto 2, Sampler: Euler a, Steps: 27, VAE: sdxl\_vae.safetensors, Denoising strength: 0.28.)

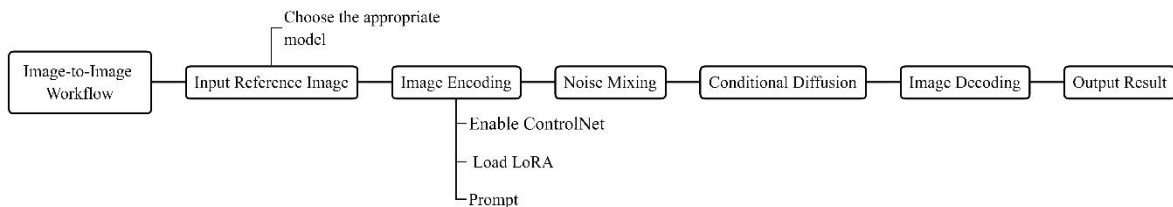


(Figure 3: Style Transformation Based on SketchUp Model)

(Image source: SketchUp model image from New Chinese Style Rural Residential Collection SU Model

Download [ID:1127426731]\_Zhumo su Model Network. Renderings: Author's drawing)

### 3.2. Technical Realization: Adapting Stable Diffusion's Core Functions



(Figure 4: Stable Diffusion Image-to-Image Workflow Diagram (Image source: Author's drawing))

- **ControlNet Plugin:** Ensures structural stability of the generated scene (e.g., building form control, spatial proportions) through multi-modal model parameter adjustments like line drawing detection, soft edge detection, depth maps, semantic segmentation, etc.

- **LoRA Fine-tuning:** Trains lightweight adaptation models for specific design styles (e.g.,

pairing with classical gardens, future cities), enhancing the diversity and professionalism of generated content.

(Model parameters: Base Model: landscapebingV10V10\_landscapebingV10, Sampler: DPM++ 2M Karras, Steps: 25, VAE: vae-ft-mse-840000-ema-pruned.safetensors, ControlNet control strength 0.85.)



(Figure 5: Spatial Rendering Generated from Scheme Line Draft)

(Image source: Line art from: <https://huaban.com/pins/3747171256>, Rendering: Author's drawing)

### 3.3. Scene Modification and Atmosphere Rendering

- **Local Iterative Optimization:** During the scheme refinement phase, perform local repainting (inpainting) on the generated renderings (e.g., replacing outdoor paving with turf, changing a swimming pool to a wooden deck) without needing to remodel, achieving the goal of modifying the image.

- **Dynamic Lighting Simulation:** Input appropriate prompts (e.g., "forest at dusk, sunlight penetrating mist forming Tyndall effect") to generate lighting effects consistent with physical laws for

reference.

- **Multi-climate Condition Testing:** Quickly generate visual effects of the same scene under different weather conditions (rain, snow, sandstorm), assisting environmental narrative design and enhancing the emotional impact of the visuals.

(Model parameters: Base Model: LWANG\_ARCH\_MIX.V0.5Fp16Fix, Sampler: DPM++ 2M Karras, Steps: 30, VAE: vae-84m-pruned\_2.0.safetensors, ControlNet line drawing control and local repainting. Control weight 1.1.)



(Figure 6: Different Environmental Spatial Renderings Generated from Scheme Line Draft)

(Image source: Line art from: Landscape Architecture Marker Pen Hand Drawing | One-Point

### 3.4. Integration with Traditional Toolchains

- **Blender Plugin:** Such as the AI Render plugin, directly imports Stable Diffusion generation results into the 3D viewport, assisting with material and lighting adjustments.

- **UE5/Unity Engine Integration:** Imports generated textures into the engine in real-time via Python scripts to test dynamic scene effects.

- **Photoshop Plugin:** Generates images based on text, supports custom resolutions. Performs style transfer or detail enhancement based on existing images. Intelligently patches missing parts of an image (requires marking repair areas with a white brush).

The core advantage of generative AI design tools lies in their ability to rapidly generate high-quality content. The intelligent production process significantly compresses the traditional design cycle. Design students can devote more energy to the preliminary creative conception and strategic

Perspective Material - Huaban Net, Renderings: Author's drawing)

optimization of the scheme. By simply inputting simple prompts, they can quickly obtain high-quality design materials, significantly improving the efficiency of the design process [8]. In addition, Stable Diffusion and MidJourney offer diverse parameter settings and style choices. Based on the model's diffusion algorithm, dynamic experiments can be conducted in dimensions such as lighting atmosphere and material texture. This "digital trial-and-error" mechanism effectively enhances the efficiency of scheme validation. It enables environmental art design students to adjust output results at any time according to requirements, generating more creative and personalized original design content, providing students with a brand-new creative experience [9]. Students can transform their ideas into visual art, thereby gaining a sense of accomplishment and satisfaction.

## 4. Conclusion and Outlook

This research focuses on the innovative practical application of generative AI design tools in educational settings, systematically verifying their revolutionary value throughout the entire process of environmental art design education. Compared to traditional design workflows, generative AI tools demonstrate three significant advantages in the stages of preliminary concept deduction, scheme text generation, spatial visualization expression, and design development: First, they assist in realizing the diverse derivation and rapid iteration of creative schemes through algorithms; Second, relying on large language models, they better identify scheme prompts; Third, they employ techniques of gradually adding noise and learning the denoising process to generate high-precision spatial renderings. Empirical evidence confirms the significant advantages of generative AI tools in improving design efficiency and stimulating creative dimensions, providing empirical support for the paradigm shift in design education. Although existing research has preliminarily explored user experience, generative AI technology, and the needs for design tools in educational settings, bringing new possibilities to design tools, their practical application in education still faces some challenges. For example, users face a relatively high threshold for operating the tools, and issues exist with the quality and consistency of generated content. Furthermore, existing research rarely focuses on the adaptability of generative AI tools in educational settings and their impact on learning outcomes. There is still a lack of systematic research framework for optimizing the functionality of design tools in educational settings. However, as the model accuracy of future AI tools increases and training data is continuously updated, the generated design images will become increasingly precise and controllable. This will drive the cultivation of design thinking from experience-led approaches towards intelligent evolution through human-AI collaboration, also providing theoretical support and practical

references for environmental art design education [10].

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